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THESIS

SIMULATION AND ANALYSIS OF CLASS A AND B TACAIR FLIGHT MISHAPS WITH AN ASSESSMENT OF HUMAN FACTORS INTERVENTION

by

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The increasing mechanical reliability of Naval Aviation (NA) aircraft has made human error (HE) the leading cause of Class A and B flight mishaps. To increase understanding of the underlying causes of HE, the Naval Safety Center in Norfolk, VA, developed the Human Factors Analysis and Classification System (HFACS). The HFACS taxonomy consists of 17 types of basic HE. This HFACS taxonomy has been used as a data analysis tool to classify 141 Class A and B Naval Tactical Aircraft (TACAIR) flight mishaps (FM) from fiscal year (FY) 90 to FY97. The study shows an important relationship between Adverse Mental State and 12 of the 17 HE types in the HFACS taxonomy. Significantly, when one of these 12 HE types is cited in an FM, greater than 70 percent of the time, Adverse Mental State is also cited as a co-causal factor in the mishap. Two other HE types have this 70 percent co-causal factor relationship with 3 of the 17 HE types. Adverse Mental State has an important relationship to the majority of the HE types in the HFACS taxonomy, compared with other HE types. For this reason, Adverse Mental State merits further investigation and should be considered in the development of HE prevention programs for Naval Aviators.

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SIMULATION AND ANALYSIS OF CLASS A AND B TACAIR FLIGHT MISHAPS WITH ASSESSMENT OF POTENTIAL HUMAN FACTORS INTERVENTION

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requirements for the degree of

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ABSTRACT

The increasing mechanical reliability of Naval Aviation (NA) aircraft has made human error (HE) the leading cause of Class A and B flight mishaps. To increase understanding of the underlying causes of HE, the Naval Safety Center in Norfolk, VA, developed the Human Factors Analysis and Classification System (HFACS). The HFACS taxonomy consists of 17 types of basic HE. This HFACS taxonomy has been used as a data analysis tool to classify 141 Class A and B Naval Tactical Aircraft (TACAIR) flight mishaps (FM) from fiscal year (FY) 90 to FY97. The study shows an important relationship between Adverse Mental State and 12 of the 17 HE types in the HFACS taxonomy. Significantly, when one of these 12 HE types is cited in an FM, greater than 70 percent of the time, Adverse Mental State is also cited as a co-causal factor in the mishap. Two other HE types have this 70 percent co-causal factor relationship with 3 of the 17 HE types. Adverse Mental State has an important relationship to the majority of the HE types in the HFACS taxonomy, compared with other HE types. For this reason, Adverse Mental State merits further investigation and should be considered in the development of HE prevention programs for Naval Aviators.

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EXECUTIVE SUMMARY

Over the past decade, 80 percent of all Class A Naval Aviation (NA) Flight Mishaps (FMs) can be attributed to human error (HE) (Naval Safety Center, 1999). In response, the Naval Safety Center (NSC) has recently adopted the Human Factors Analysis and Classification System (HFACS) model and is studying HE more thoroughly (OPNAV 3750.6R). Previously, the NSC studied HE primarily by classifying it in a "who? what? and why?" format (OPNAV 3750.6R). This classification, not developed under any specific theoretical framework of human performance, proved difficult to infer any specific causes of HE to a FM (Shappel & Wiegmann, 1997). The recent introduction of the theoretically based HFACS by the NSC (1997) provides a sounder framework for the study of HE (Reason, 1990).

The occurrence of HE has been studied considerably (Reason, 1990). Naturally, psychologists tend to study HE from the standpoint of their own psychological disciplines, which leads to conflicting views of the underlying causes of HE (Senders & Moray, 1991). Because of this variance in the different theoretical approaches to the study of HE, the U.S. Navy has invested a great deal of time and effort in the development of HFACS for the classification of HE in Naval Aviation (Shappel & Wiegmann, 1997). The basic aim in the study of accidents involving HE should be to prevent similar accidents from reoccuring by anticipating problems in similar situations (Pimble & O'Toole, 1982).

There are four identified layers of causation in the HFACS model:

1) Organizational influences composed of latent failures,
2) Unsafe supervision composed of latent failures,
3) Preconditions for unsafe acts composed of active and latent failures,
4) Unsafe acts composed of active failures (OPNAV 3750.R).

Active failures are those HEs the pilot has direct control over at the time of the FM and latent failures are causal factors which the pilot has no direct control over at the time of

the FM. The four layers of causation are composed of 17 total types of basic HE that define the HFACS taxonomy.

This study involves the analysis of an existing database of Class A and B flight mishaps among Naval Aviation Tactical Aircraft (TACAIR) citing HE as the primary causal factor in the flight mishap. In 1998, Naval Aviation Psychologists at the NSC took the Class A FMs from fiscal year (FY) 90 to FY98 and classified them according to the HFACS taxonomy. The Class B flight mishaps from FY90 to FY98 are classified according to the HFACS taxonomy by the author, using the Mishap Investigation Reports (MIRs) description of the causal factors in the FM. There were 122 Class A TACAIR flight mishaps and 19 Class B TACAIR flight mishaps from FY90 to FY97 categorized as human factors flight mishaps. For FY98, there were 12 Class A TACAIR FMs and 0 Class B TACAIR FMs identified as human factors flight mishaps.

The purpose of the data analysis is to determine any important relationships between the 17 basic types of human error in the HFACS taxonomy and to verify that the accident arrival rate for the Class A and B TACAIR human error flight mishaps is from a Poisson distribution. The development of a simulation model to analyze the predicted future occurrence of HE types in the HFACS taxonomy is accomplished. In order to explore the dataset and to analyze the sets of flight mishaps associated with each causal factor, the analysis of the sets consisted of studying the intersection of sets between causal factors. The most important relationships are found in multiple set intersections of HFACS HE types. It is here that "Adverse Mental State" is identified as an important causal factor. Adverse Mental State has an important relationship in 12 of the 17 basic types of HE in the HFACS taxonomy. When one of these 12 HE types is cited in an accident, greater than 70 percent of the time, the investigation also cites "Adverse Mental State" as a causal factor.

By modeling accident and flight hours for FY90 to FY97 in a log linear model, the accident arrival rate is determined to be Poisson. The significance of "Adverse Mental State" is further established by the results of the simulation. The only important multiple HE types in the simulation were those paired with "Adverse Mental State." Important HE

types were determined to be significant if the 95 percent confidence interval calculated from the simulation run did not contain zero.

Due to the inherent complexity of the study of human error, making recommendations for its reduction, based on a HE type that shows an important relationship with multiple HE types, is the best approach. Single HE type recommendations do not take into account the interaction that causal factors undoubtedly have in a flight mishap. Any program to reduce human error should concentrate on an influential HE type related to as many types of human errors as possible. This program should be a one- to two-hour program, requiring aviators to attend annual or semi-annual presentations to maintain their awareness of program issues. Given the strong relationships between "Adverse Mental State" and the majority of the other HE types in the HFACS taxonomy, establishing a human error flight mishap awareness and reduction program based on "Adverse Mental State" would be appropriate.

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I. INTRODUCTION

Over the past decade, approximately 80 percent of all Class A Naval Aviation (NA) Flight Mishaps (FMs) have been attributed to human error (HE) (Naval Safety Center, 1999). Although mechanical failure is an important causal factor in FMs, the accident rate for mechanical failure is decreasing. Apparently, HE has reached a plateau and shows no signs of change (Nutwell & Sherman, 1996). Various models and taxonomies have been used to study HE and its causes (Shappell & Wiegmann, 1997). These include cognitive information processing models, models of cognitive malfunction and models of unsafe acts. These models are essential for studying HE at the individual operator level; however, the study of HE must also include organizational, supervisory and environmental influences to allow the human factor analyst to understand such accidents in their entirety (Shappell & Wiegmann, 1997).

As previously stated, the current Class A FM rate in NA has human factor accident rates attributable to pilot and supervisory error as high as 80 percent. This rate is of great concern to the Navy which created a Human Factors Quality Management Board (HFQMB) to look specifically into reducing the rate of human factors accidents in NA (Nutwell & Sherman, 1997). The majority of Naval Aviation human error FMs occur due to the direct or indirect actions of pilots and their supervisors. Any reduction of FMs due to HE would result in savings in both lives and equipment.

The Naval Safety Center (NSC) has recently adopted the Human Factors Analysis and Classification System (HFACS) model (OPNAV 3750.6R) to meet the requirement to study HEs more thoroughly. Previously, the NSC studied HE primarily by classifying it in a "who? what? and why?" format (OPNAV 3750.6Q). Because this classification was not developed under any specific theoretical framework of human performance, it proved extremely difficult to infer any specific causes of HE (Shappel & Wiegmann, 1997). The recent introduction of the theoretically based HFACS by the NSC (1997)

provides a sounder framework for the study of HE (Reason, 1990). The HFACS taxonomy for classifying HE allows for a clear representation of the root causal factors of HE in an accident. Once these factors are identified, they can be studied in a cognitive psychological context. More importantly, potential intervention strategies can be evaluated based on the factors identified. The future impact on accident frequency and costs can be assessed using intervention strategies. In order to develop specific intervention strategies, one must determine if any of the identified causal factors in the FMs are important. The intent of this thesis is to identify these important HEs in Naval Aviation FMs through statistical analysis and to recommend intervention strategies.

A. BACKGROUND

The Naval Safety Center, which is located at the Norfolk Naval Air Station, Virginia, has three directorates: aviation, afloat and shore safety, and five support departments (NSC, 1997). The directorates work both independently and as a team to help the Chief of Naval Operation and the Commandant of the Marine Corps prevent operational FMs, promote safety, and monitor safety programs. Through their involvement in all phases of safety, the NSC develops recommendations for formulating safety policies to maintain the highest level of combat readiness. The prevention of HE has been identified as one of the biggest remaining challenges for NA safety (Nutwell & Sherman, 1996). With a thorough study of the HE involved in Naval Aviation FMs, safety policy can be developed, which would further the goals of the NSC.

The NA directorate implements the Naval Aviation Safety Program (OPNAV 3750.6Q) supervised by the Assistant Chief of Naval Operation (Air Warfare). The NA directorate maintains a repository for all reports and related data for aircraft FMs and conducts NA statistical research, studies, special projects, analyses and compilations of aircraft FMs (NSC, 1997). The Naval Aviation Safety Program also directly or indirectly assists in investigations into hazards and FMs. Their purpose is to preserve human and material resources through policies that prevent similar FMs and eliminating known hazards. NSC personnel also conduct safety inspections and surveys at operational

commands to evaluate the command's safety programs and practices and to make recommendations for improvements.

Previous Naval Postgraduate School (NPS) theses in support of the NSC found a relationship between human factors and accident causation (Lacy, 1998; Schmorrow, 1998; Sciretta, 1999; Teeters, 1999). These theses demonstrated that analyzing human factors is a highly relevant issue to reducing all Naval Aviation flight mishaps. Lacy (1998) examined major mishaps afloat, Sciretta (1999) looked at electrical mishaps afloat, Schmorrow (1998) studied reportable NA maintenance related mishaps and Teeters (1999) contrasted major and minor maintenance related mishaps with one Wing. The common thread between each of these studies is the conclusion that human factors account for a large majority of Naval mishaps when the causal factors involved in the accidents are studied. Each author successfully modeled arrival rates of human error accidents and subsequently hypothesize the projected monetary savings to the Navy by varying the accident arrival rate in the models.

B. OBJECTIVES

The primary purpose of this study is to conduct a statistical analysis to identify patterns in NA Class A and B TACAIR human factor flight mishaps. Moreover, the author, after identifying these patterns, will determine which patterns warrant further analysis. Then through a simulation model, these patterns will be evaluated for statistical significance. Finally, the author will identify and evaluate effective intervention strategies.

C. PROBLEM STATEMENT

Currently a formal process of studying HE in NA has not been fully integrated into the investigation of flight mishaps. The validation of the HFACS classification taxonomy, through statistical analysis, may emphasize the importance of formally integrating HFACS into the accident investigation process. By studying Class A and B flight mishap Mishap Investigation Reports (MIRs), one can model the occurrence of

aircraft FMs, can identify potential intervention strategies for aircraft FMs due to HE, and can forecast these strategies impact on future FM frequencies. By employing current human factors theory, including the classification of all human factors FMs studied using the HFACS taxonomy, and by applying the data analysis to the NA Tactical Aircraft (TACAIR) FMs, intervention strategies can be proposed. This would save both lives and valuable resources through a reduction of human factors flight mishaps. This study investigates the following questions:

1) Can human factor trends be identified using the HFACS taxonomy of HE?

2) Can potential intervention strategies be identified for the primary human factors trends found?

3) Can the intervention strategies identified be used in the Class A and B FM models to evaluate their subsequent impact on FM frequency and costs?

D. DEFINITIONS

This study uses the following definitions (OPNAVINST 3750.6Q, 1991):

1) **Class A Mishap**. A mishap in which the total cost of property damage (including all aircraft damage) is $1,000,000 or greater; or a naval aircraft is destroyed or missing; or any fatality or permanent total disability occurs with direct involvement of naval aircraft (OPNAVINST 3750.6Q, 1991).

2) **Class B Mishap**. A mishap in which the total cost of property damage (including all aircraft damage) is $200,000 or more, but less than $1,000,000 and/or a permanent partial disability, and/or the hospitalization of five or more personnel (OPNAVINST 3750.6Q, 1991).

3) **Tactical Aircraft (TACAIR)**. The following Naval Aircraft are considered as TACAIR for this study: A-4E, A-4F, A-4M, A-4Q, A-6A, A-6B, A-6E, A-7B, A-7C, A-7E, A-7F, AV-8B, AV-8D, EA-6A, EA-6B, EA-7L, F-4A, F-4G, F-4J, F-4N, F-4S, F-5E, F-5F, F-9F, F-14A, F-14B, F-14C, F-14D, F-16N, F-18A, F-18B, F-18C, F-18D, F-18E, F-18F, KA-6B, KA6D, OA-4M, RF-18A and RF-4B.

E. SCOPE AND LIMITATIONS

The scope of this study encompasses all Naval TACAIR Class A and B FMs citing human factors as the primary causal factor of the FM between October 1, 1989, and September 30, 1997. It examines the classification of HE in Naval TACAIR FMs, using the HFACS taxonomy. An introduction to the history of the study of HE, the genesis of the NSC's HFACS, and the use of human factors in Naval Aviation accident investigation is discussed in Chapter II. Chapter III provides a framework of the methodology used in the study. Chapter IV covers a data analysis of the HFACS taxonomy, a modeling of the accident arrival rate, and a modeling of the rates of future HE occurrences, as defined by the HFACS taxonomy. Concluding the study, Chapter V contains a research summary, discussion and recommendations.

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II. LITERATURE REVIEW

There has been considerable study into the occurrence of human error (HE) in terms of why we make mistakes that lead to accidents (Reason, 1990). Though there has been much interest in HE by many researchers and authors, there is a lack of agreement in the field of HE in regard to a proper definition of error (Senders & Moray, 1991). This lack of agreement is an issue, which makes the study of HE difficult.

Psychologists tend to study HE from the vantage point of their psychological disciplines, which leads to different views of the underlying causes for human error (Senders & Moray, 1991). These differences in the study of human error create alternative theoretical avenues from which the study of HE is approached. Numerous industry specific taxonomies are applied by researchers to their own areas of interest. Most of these taxonomies are based on the concept of endogeneous and exogenous causes of HE, those that have their origin, inside or outside the person (Senders & Moray, 1991). Even with the commonality of endogeneous and exogenous causes of HE, taxonomies cannot be easily transferred from one area of study to another. For example, taxonomies used to model accidents in the nuclear energy industry are difficult to transfer to the study of NA accidents. The theoretical underpinnings of these different taxonomies often do not allow them to be compared directly with other taxonomies, leading to slight theoretical disagreements regarding the various models of HE causation.

Because of the variance in the different theoretical approaches to the study of HE, the U.S. Navy has invested a great deal of time and effort in the development of a specialized taxonomy for the classification of HE in Naval Aviation (NA) (Shappel & Wiegmann, 1997). In pursuit of this specialized taxonomy and to insure consistency of internal studies into human error, the Navy has decided to base its studies of HE on "The Taxonomy of Unsafe Operation" (Shappel & Wiegmann, 1997) a single taxonomy of HE based on extensive research into human behavior appropriate to the Naval Aviation

community. This classification system is currently called the Human Factors Analysis and Classification System (HFACS).

A. HUMAN ERROR

The basic aim in the study of HE accidents should be to prevent similar accidents from occurring again and anticipate and avert hazardous situations (Pimble & O'Toole, 1982). For an empiric study of human error, a commonly accepted definition of HE must exist. This has been one of the issues plaguing the study of human error. Few researchers define human error identically. Some authors do not even accept a definition for human error (Senders & Moray, 1991). Their beliefs are grounded in Freudian psychology, believing that there are no accidental errors--everything is either subconsciously or consciously driven (Senders & Moray, 1991). However, the majority of those who study human error have a more tangible definition of HE. They do not view human error as a subconciously driven expression of the individual, but simply as a mismatch of intention and action (Senders & Moray, 1991).

For the Freudian camp, the explanation of human error would follow this manner of logic: An actor in a given scenario is supposed to lower the landing gear of an aircraft in-flight, but unintentionally (at least consciously) fails to do so and lands gear up. Since Freudian theorists do not accept unintentional causal factors, the actor must have willfully done this subconsciously (Reason, 1990). Why would the actor fail to perform such a vital action in the landing sequence? A Freudian explanation would proceed as follows: Internally, the actor has a subconscious conflict between the inherent risk of the NA profession and a long-term commitment to his or her family. Consciously, the actor cannot arbitrate between these conflicting issues. As a result, subconsciously, the actor decides to "quit" flying one way or another. The next day while he is landing, the actor's subconscious intentionally wills the conscious to forget to lower the landing gear. All this occurs because the actor could not consciously decide to quit flying even though in reality his or her preference is to quit. Fortunately, the majority of those who study HE

do not base their studies on Freudian philosophy. This approach to the study of human error would make predicting HE extremely complex, if not impossible.

Certainly, although the majority of authors do not agree on a proper definition for human error, they at least accept the existence of HE (Senders & Moray, 1991). Generally they accept a broad-based definition; "When one interacts with machines or complex systems, one frequently does things contrary to intention" (Senders & Moray, 1991). Many of the differences between researchers occur in the taxonomy of human error which they use in their study.

Kollarits (1937), examining approximately 1,200 human errors committed by himself, his wife and his colleagues, conducted one of the earliest studies of human error. Proposing an initial fourfold classification based on the superficial appearance of the HE, Kollarits used a taxonomy of substitution, omission, repetition and insertion. Kollarits observed that sometimes assigning a HE unequivocally to a single category was difficult (Senders & Moray, 1991). This foreshadowed the classifying of HE types for most of the mainstream practitioners. Unlike the Freudian approach, the mainstream approach to the study of human error breaks the causal factors of HE into multiple parts, based upon the conscious decisions made by actors in the decision-making process.

Breaking this human error into its atomic parts is the root of many differences in the definition of human error. The definition of a human error certainly depends on the point of view of the person judging whether a HE has occurred (Park, 1995; Senders & Moray, 1991). The individual committing the human error recognizes the error only after it has occurred thus, the individual's perspective is only hindsight. Herein lies a portion of the dilemma of defining human error. What if the HE occurs without creating instability in the system? In this situation, many researchers studying human error would contend that no HE had occurred (Senders & Moray, 1991).

Recalling the landing gear example discussed earlier, reconsider this incident following the more mainstream ideals of human error. What if the actor decides to lower the landing gear, reaches for the landing gear, and grabs it, but then the aircraft's airspeed enters his peripheral vision. This cues the actor to focus on the airspeed, the actor notices

that the airspeed is too fast to lower the landing gear safely. At this point, the actor delays lowering the gear until the aircraft slows to the correct airspeed to lower the gear. Has a HE been made in this circumstance? Those who would say "yes" would contend that a HE had occurred because the actor had erred simply by reaching for the landing gear. Those researchers who would argue that a human error had not occurred in this situation, approach HE from a less rigid viewpoint (Senders & Moray, 1991). They would say that since the actor recognized this incorrect action before it adversely affected the system, a human error had not occurred.

For a thorough in-depth understanding, the best study of human error would be to approach the study of HE from the purists' view (AGARD, 1998). At a minimum, such a study would require each aviator to maintain a human error diary of every flight (Lourens, 1990). This study also could not be short-term. It would need to follow aviators throughout their careers. Obviously, not only would this study be full of inaccuracies, due to self-reporting, but collecting and analyzing all this data would be highly expensive. Moreover the aviators would likely be disinclined to report their faults (AGARD, 1998). Such a study would most likely be received with a great deal of distrust.

Researchers of human error in Naval Aviation must therefore rely on data gathered on reportable incidents of HE (AGARD, 1998), i.e. required to be reported by the letter of the law. Consequentially, they take the theoretical viewpoint of HE as having a tangible outcome, affecting the correct operation of the system. To ensure consistent results, either an actor or an external analyst needs a model of task performance in order to decide whether an action has been correctly executed. This leads to HE being defined as a human action that fails to meet an implicit or explicit standard. A HE occurs when a planned series of actions fail to achieve a desired outcome and when this failure cannot be attributed to the intervention of some chance occurrence (Senders & Moray, 1991).

In aviation, a human error can be defined as an action or event with an effect that is outside specific tolerances required by a particular system. The definition does not directly refer to actions of the pilot but only to the consequences of the pilot's actions (Reason, 1990). Even if the actor intended to do "A" and instead did "B," there would

have been no human error unless the system had exceeded acceptable limits (Senders & Moray, 1991). Clearly, if an accident does not occur, researchers cannot study it. In many of the taxonomies of human error, the researcher's studies start here. Their taxonomies are used to separate these accidents into specific types of human error and to study them to provide insight into preventing future HE accidents.

Human error can be seen as a necessary and natural part of skill development (Lourens, 1990). Human error, as such, is always part of control operations that include feedback. In such situations, HEs are neither good nor bad (Wickens, 1991; AGARD, 1998). When human errors become too large, badly timed or hazardous, they become "grievous human errors." A "grievous human error" occurs when the actor exceeds safe operating tolerances (Senders & Moray, 1991). In order to advance in skill and knowledge people must commit errors to advance their abilities. Human error is needed for learning, adaptating, creating and surviving. Human error may result in a destructive outcome, but there may be virtue in these HEs if they result in learning and their negative consequences can be minimized. Human errors are the inevitable results of actors creatively experimenting with their environment and are necessary for gaining knowledge and improving one's skills (Neville, 1991).

B. TAXONOMIES

If HE is to be studied empirically, there must be a commonly accepted theory of normal behavior (O'Hare, Wiggins, Batt & Morrison, 1994). In a passage from the *Principles of Psychology* (1890) William James said, "Habit diminishes the conscious attention with which our acts are performed." In this early passage, James is referring to "schema," an important part of understanding normal behavior. Schema is one of two important processes mentioned by Reason as important when developing a framework so that one can understand human cognition (normal behavior) (Reason, 1990). Reason mentions two control modes for cognition: attentional and schematic. These two modes are found in most frameworks that outline human cognition and HE. The attentional mode is defined as conscious processing and the schema mode is defined as automatic or

unconscious behavior (Wickens, Gordon & Liu, 1997). Cognitive activities and normal behavior in everyday tasks are guided by a complex interplay between these two modes of cognitive control (Reason, 1990).

The "attentional-control-mode" is related to working memory and consciousness (Wickens, 1991). This mode is limited, sequential, slow, effortful and difficult to sustain for more than brief periods (Dosher & Sterling, 1986). It can be thought of as the chalkboard we work on cognitively. A very limited amount of information is assimilated. This process is controlled in a conscious and largely voluntary manner. Since more than one high-level activity may be available for processing at any one time, the selection process used by the operator becomes very important. Much of the attentional mode's work is concerned with setting future goals, with selecting the means to achieving them, with monitoring progress toward their objectives, and with the detection and recovery of HEs (Reason, 1990).

The "schematic-control-mode" is not consciously brought to bear on activities (Wickens, Gordon & Liu, 1997). As William James said, "Habit diminishes our conscious attention to a task." This is the development of the operator's schema. When people intend to do something, they think about their intended actions, called "planning ahead" or "forethought." For a pilot who has flown a particular flight profile numerous times, actions become automatic (Bond, Bryan, Rigney & Warren, 1960). The schema developed by the aviator allows an increase in the efficiency with which the aircraft is flown. This allows the pilot to think ahead of the aircraft because he or she does not have to dwell on the minutia of action or reaction in the operation of the aircraft.

As an example, the actor from the earlier example is flying and decides to enter a steep angle of bank. Early in an aviator's career, this can be a difficult manuever, requiring the complete focus of the attentional control mode on this single task (Wickens, 1991). This requires the actor to consciously recite a rote mnemonic to force attention from one flight instrument to the next to execute the manuever properly. For the novice, this manuever uses all the available resources of the attentional control mode. For the experienced actor such a manuever is barely noticed consciously, except for setting the

parameters correctly for the entry into the manuever (Hart & Sheridan, 1984). This manuever requires very little use of the actor's attentional control mode, which is a limited resource, allowing these resources to be focused on planning issues instead of basic manuevers. For the expert, an organized unit of knowledge, the schema, is activated to accomplish the manuever (Reason, 1990). Many of the taxonomies on HE in some way incorporate these ideas of attentional control and a schematic control mode.

A number of models have brought insight and value to the study of HE (Senders & Moray, 1991). James Reason provides a compilation of some of the most influential taxonomies in the study of human error (Reason, 1990). The Norman-Shallice model represents a family of action theories. Rasmussen's "skill-rule-knowledge" framework models cognitive control processes. Rouse's "fuzzy rule" model is based on the assumption that humans are not truly optimizers in their thought processes. Baar's global workspace (GW) model focuses on interaction within working memory. Reason's generic HE modeling system (GEMS) builds its structure around Rasmussen's ideas of skill-based slips and lapses, rule-based mistakes, and knowledge-based mistakes for HE classification (Park, 1994). The Helmreich model attempts to go further in the study of HE by focusing outside of operator human error. Four concentric circles represent Helmreich's model with operator error at the innermost circle, which is influenced by external factors in the outer circles. Each of these taxonomies has had an impact on the way human error is viewed in the particular industrial applications for which the taxonomy was developed. The study of HE in Naval Aviation draws a little from each but focuses mainly on the studies by Rasmussen and Reason for the development of an aviation specific taxonomy. The NSC's Human Factors Analysis and Classification System (HFACS) uses theoretical constructs from both Reason and Rasmussen in modeling human error.

1. Norman-Shallice's Attention to Action Model

Norman and Shallice developed an attention to action model, which provides for two kinds of control structures, horizontal threads and vertical threads (Norman &

Shallice, 1990). The model is based upon the idea that an adequate theory of human action must account for not only correct performance, but also for the more predictable varieties of human error. Systematic HE form and correct performance are seen as two sides of the same theoretical coin (Reason, 1990).

The control system proposed by Norman and Shallice is clearly related to the attentional- and schema-control-mode view of human error (Norman & Shallice, 1990). The horizontal threads are each composed of a self-sufficient strand of specialized processing structures (schema). The vertical threads interact with the horizontal threads giving the means by which attentional or motivational factors can change the schema activation values. Horizontal threads govern habitual activities not requiring the need to receive constant attentional control, triggered by environmental input or previously active schemas. Higher level attentional processes come into play through the vertical threads, in unique or critical situations when currently active schemas are insufficient to achieve the current goal. This adds to or decreases schema activation levels to modify ongoing behavior. Norman and Shallice also include motivational variables which they view as influencing schema activation along the vertical threads, but motivational variables are assumed to work over much longer time periods than the attentional resources (Reason, 1990).

An example of the interaction between vertical and horizontal threads could be the previously discussed experienced actor flying into the airport traffic pattern. As the actor enters the landing pattern, active horizontal threads (schemas) allow the actor to control many variables without continuously monitoring them. Without warning, the actor notices flocks of birds in the aircraft's flight path. In this critical situation, a vertical thread (attentional-control-mode) activates an evasive manuever schema contained in a horizontal thread. This allows the actor to execute quickly a series of control manipulations, without having to use his or her attentional-control-mode, to avoid the hazard.

2. Rasmussen's Skill, Rule and Knowledge System

Like Norman and Shallice's, Rasmussen's (1982) "skill-rule-knowledge" model of cognitive control mechanisms is also human error oriented. Rasmussen was more interested in studying fatal human errors specifically. The framework of the model is based on the study of those in supervisory control of industrial installations, particularly during emergencies in hazardous process plants. The highly familiar, "skill-rule-knowledge" framework originated from a verbal protocol study of technicians engaged in electronic trouble shooting in a study by Rasmussen and Jensen in 1974.

Three levels of performance correspond to decreasing levels of familiarity with the environment or task (Reason, 1990). Skill-based performance is governed by stored patterns of behavior also known as schema (Park, 1994). The skill-based levels of action are vulnerable to failures of attention and memory. Rule-based performance is applicable to tackling familiar problems in which solutions are governed by stored rules of the type:

if (state) then (diagnosis) or if (state) then (remedial action)

(Wickens, Gordon & Liu, 1997). Rule-based performance is also comparable to Norman & Shallice's interaction between vertical and horizontal threads, where the attentional-control-mode is used in identifying the problem to be solved and stimulating specific problem-solving schemas. An example of this would be a pilot's reaction to an in-flight emergency. The pilot uses attentional resources in identifying the perceived emergency and responds with a practiced response, schema, to the identified emergency.

Human errors at the rule-based level are typically associated with the misclassification of situations leading to the application of the wrong rule or the incorrect recall of procedures (Reason, 1990). Knowledge-based issues of HE come into play in novel situations for which actions must be planned on-line, using conscious analysis (attentional-control-mode) and stored knowledge (Wickens, Gordon & Liu, 1997). Human errorss at this level arise from resource limitation and incomplete or incorrect knowledge. With increasing expertise, the primary focus of control moves from

knowledge-based toward the skill-based levels but all three levels can co-exist simultaneously (Reason, 1990).

According to Reason, Rasmussen's major contribution in his model for the theory of HE in cognitive processes is how he theorizes the interaction of the operator's cognition and the levels of human error (Reason, 1990). Rasmussen charted the shortcuts that human decisionmakers take in real-life situations, known as the "Step-Ladder" model (Park, 1994). Instead of a linear relationship in decision-making as most decision theorists had represented, Rasmussen's model is analogous to a stepladder, with the skill-based activation and execution stages at the bases on either side and the knowledge-based interpretation and evaluation stages at the top. Intermediates on either side are the rule-based stages (Reason, 1990). Shortcuts may be taken between these various stages, usually in the form of highly efficient but situation specific stereotypical reactions. Where the observation of the system's state leads automatically to the selection of remedial procedures, without the slow and laborious intervention of knowledge-based processing. This stepladder layout also allows for associative leaps between any of the decision stages. This strategy can also increase a person's vulnerability to making HEs because the strategy is overly reliant on the appropriateness of past experience (Park, 1994).

Using, again, the previous actor as an example, human error can be looked at in terms of "skill, rule and knowledge" based cognitive processes. Skill-based errors will occur when the actor is in a familiar environment. As an example, the actor is taxiing an aircraft at his or her homebase (very familiar surroundings and routines). New construction, however, has rerouted the actor's familiar patterns of returning to his squadron. After landing, the pilot turns onto the closed taxiway and damages the aircraft's engine, due to debris on the closed taxiway.

Rule-based errors will occur when the aviator does not have a lot of experience in a variety of unique and common situations. Experienced aviator's avoid rule-based errors because of his or her exposure to multiple experiences. Rule-based human errors are going to occur in the form:

if (state) then (diagnosis) or if (state) then (remedial action)

types of rule-based behavior. Knowledge-based errors occur when the aviator decides to execute a plan and the plan turns out to be inappropriate for the situation. An example is a poor approach choice in bad weather. Once the actor commits himself to the approach and enters the weather, his skills may be exceeded and a human error flight mishap (FM) could ensue.

3. Rouse's "Fuzzy Rule" Model

Rouse (1981) in developing his "fuzzy rule" model attempted to bring computer based modeling of HE to bear on the problem of prediction. Rouse uses rules based upon concepts of artificial intelligence. The model attempts to model human cognition by trying to codify the way human memory encodes stores and retrieves a limitless set of schematic representations. Assuming that knowledge is based on a rule-based format, a necessary assumption for modeling an artificial intelligence system, Rouse distinguished two types of problem-solving rules: symptomatic strategy (S-rules) and topographic search (T-rules) (Reason, 1990). For Rouse's decisionmakers, they can either use an S-rule or T-rule to solve a problem. For the S-rule, identification of the problem is derived from a match between local system cues and a stored representation of a pattern of indications of a failure state in the system. In keeping with the flavor of the artificial intelligence approach Rouse brings to the model, S-rules are frequently used in a rule-based form with some appropriate remedial diagnoses.

As an example of an S-rule, using the aviating actor from the previous example:

if (the landing gear handle is down and all the lights are not illuminated for gear down indications), then (check the hydraulic pressure gauges).

The T-rules need not contain any reference to specific system components but instead require access to a mental or actual map of the system. T-rules also require consideration of the structural and functional relationships between their constituent parts. An example of the T-rule is based more on a predicate calculus approach to the problem at hand:

if (the functioning of X is faulty and X depends on Y and Z, and Y is known to be working), then (check Z).

The use of S-rules and T-rules as the theoretical underpinning of his model allows for easy access to programming in artificial intelligence. A list of Rouse's rules could easily be transferred to computer languages, such as LISP or PROLOG, and then used to model human behavior and from there if statistically significant, to predict HE in various situations.

4. Baar's Global Workspace (GW) Model

Baar's (1988) construction of his global workspace model is another that parallels the schema and attentional-control-mode research. Baar explains the multiple pairs of apparently similar phenomena that seem to differ in the fact that one is conscious (attentional) and the other is not (schema). Baar concentrates on what is termed the "global workspace," a working memory that allows for interaction of specialist processors (Reason, 1990). These processors compete for access to the global workspace based on their current activation level. The operators' consciousness reflects the current contents of the global workspace. Baar's global workspace model is closely identified with short-term memory and the limited capacity components of the cognitive system, concentrating more on the attentional control mode discussed earlier and how it interacts with the schema.

Baar's Global Workspace model does not extend as far as the others but looks primarily at the attentional-control-modes and their interactions. Working memory is limited and the actor can only maintain a limited amount of information in Baar's GW model. Let us take an example from our previous actor and look at it in terms of the GW, through which only a limited amount of information can be actively processed. If the actor is being given specific unfamiliar instructions while in flight, the majority of the total workspace available in the GW is used. If an event with a higher priority comes to the attention of the GW, such as a warning light, the warning light has a higher activation level than anything currently in the global workspace. This higher activation level displaces the currently active items in the global workspace and allows the GW to give full attention to the warning light.

5. Generic Error Modeling System (GEMS)

The Generic Error Modeling System (GEMS) by Reason (1990) is another rule-based type model using the ideas of attentional-control-modes and schema. Reason borrows heavily from Rasmussen's "skill-rule-knowledge" model but additionally attempts to locate the possible origins of these basic HE types. The GEMS model addresses cognitive human error. By addressing the cognitive factors instead of environmental or context-related factors, one can expect that the human error classification in GEMS will be applied to the analysis of HE in a variety of industrial situations (Park, 1994).

Reason distinguishes between three separate performance levels for the model, *skill-based, rule-based* and *knowledge-based* levels. Skill-based performance is based on sensorimotor performance, taking place without conscious control. Rule-based and knowledge-based performance come into play only after one becomes consciously aware of a problem. In this sense, skill-based errors generally precede the detection of a problem and rule- and knowledge-based errors arise during subsequent attempts to find a solution. In regards to control modes, skill- and rule-based levels of performance are related to schematic modes of control, and knowledge-based levels of performance are

related to attentional-control-modes. The GEMS model attempts to present an integrated picture of the HE mechanism operating at all three levels of performance. A main assertion of GEMS is that when confronted with a problem, people are biased strongly to search for a familiar schema. This occurs at the rule-based level, before one attempts to solve the problem at the more demanding attentional knowledge-based level. This is true, even if the individual attempted to solve the problem at the knowledge-based level to start with (Reason, 1990).

The GEMS model parallels closely the example of Rasmussen's (1982) "skill, rule, knowledge" based HE taxonomy. The difference is that Reason (1990) hypothesizes that an actor presented with a problem first attempts to solve the problem at the less attentionally demanding schema level. The actor in this situation attempts to use a familiar schema that has worked in the past to solve a similar problem. As an example, suppose that during aerial combat, the actor consistently relies on an effective high "g" manuever to disengage from an opponent. Then in the future if the actor finds himself in a position requiring a manuever of last resort to disengage from his opponent, he relies on the high "g" manuever prior to attempting anything else required to disengage from the aerial combat.

6. The Helmreich Model

The Helmreich Model approaches accident investigation into HE as a grouping of separate environments (Zotov & Dmitri, 1996). The intent of the model is to be a crew-centered study to accident causation and external factors are studied for their influence on the crew involved in the flight mishap. These separate environments are grouped into concentric circles, each affecting those they encircle. The theory of the model is that in reality the interaction and entanglement of multiple factors result in an accident (Zotov & Dmitri, 1996).

The innermost circle, the crew environment, concerns issues regarding the crew's interaction, communication, personalities and Crew Resource Management. Encompassing this circle is the physical environment in which the crew operates, issues,

such as aircraft idiosyncrasies, defects and performance characteristics, the weather, both local and general, and the airport environment. Outside of these factors is the organization that purchases and maintains the aircraft, trains the crews, and is supposed to support their actions. Surrounding these concentric circles is a regulatory environment in which regulatory action should ensure safe standards of operation (Zotov & Dmitri, 1996). The Helmreich Model views the breakdown of human error in accidents as a web of entangled strands of HE, attaching causal factors at different points within the concentric circles. Frequently researchers debate whether an accident is the result of a chain of events. The Helmreich Model theorizes that the accumulation of factors, rather than a single linkage of chained events can cause an flight mishap. Accidents, seldom occuring in isolation, are more likely to happen as a complex web of events, culminating in the accident (Zotov & Dmitri, 1996).

Looking at the previous examples, all the models have been centered on the actors and their actions or inaction. Helmreich brings into focus outside influences on the actor that influence what occurred in the flight mishap. As an example, consider an aviator involved in an FM where fatigue is the main causal factor cited in the flight mishap. To understand fully the main causal factor of the FM, the investigator must look outside of the aviator to the environment that effects him or her. Other factors just as important to the FM are: poor diet, weather, lack of proper supervision or proper leadership in the organization. All these items may play an integral role in the FM, in addition to the aviator's direct role in the flight mishap.

C. HUMAN FACTORS ANALYSIS AND CLASSIFICATION SYSTEM

The Naval Safety Center's "HFACS" is a taxonomy developed specifically for NA (Shappel & Wiegmann, 1997). Influencing the HFACS taxonomy are many of the taxonomies discussed above. HFACS uses the theoretical basis for HE described by both Rasmussen and Reason in terms of skill-based, rule-based and knowledge-based levels of performance. As in Helmreich's model, HFACS theorizes that accidents do not occur in isolation but are often the result of both internal and external influences like supervisory

and organizational HE contributing to the accident. This taxonomy also incorporates the "Domino Theory," introduced by Heinrich (1980). Heinrich's theory proposed that accident causation is not singular but has many links in a chain to a tragic human error. Anywhere in this line of dominoes, someone could remove a causal domino to prevent that final, fatal domino from falling (Shappel & Wiegmann, 1997). Of course, as discussed by Helmreich, the solution may not be as simple as removing a single domino in the accident sequence to avert a flight mishap. Although the domino may be attached in the line of accident causation, a strand in the web of causation could bypass this particular domino, and even though the domino is removed a continuity in the chain of events may still exist. In a human-factors-accident, research shows that complexity is the norm (Zotov & Dmitri, 1996).

There are four identified layers of causation in the HFACS model:

1) Organizational influences composed of latent failures,
2) Unsafe supervision composed of latent failures,
3) Preconditions for unsafe acts composed of active and latent failures,
4) Unsafe acts composed of active failures (OPNAV 3750.6R).

Active failures are those HEs the pilot has direct control over at the time the FM occurrs, and latent failures are those causal factors the pilot has no direct control over at the time the FM occurrs. The HFACS taxonomy is illustrated by the "Swiss Cheese" model of HE causation, adapted from ideas of James Reason. The illustration is composed of four integrated overlapping layers that affect the final HE, which results in an accident (Figure 1). The main point of HFACS is that HE is not studied as it is in the GEMS model. The GEMS model studies the operator level alone, but HFACS instead looks upward, as in the Helmreich Model, realizing that there may be multiple contributing factors to unsafe acts performed by the operator.

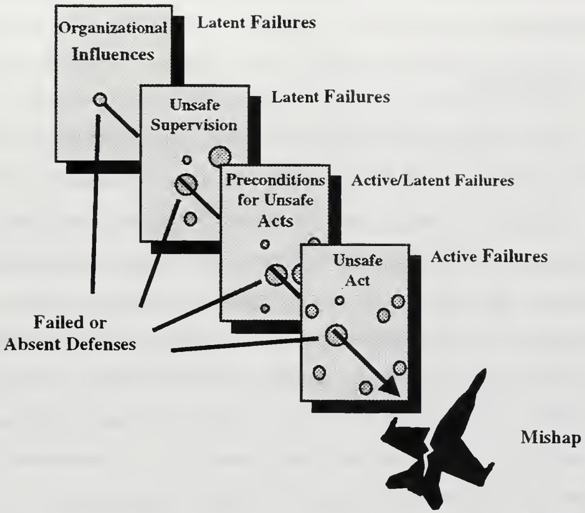

Figure 1. The "Swiss Cheese" Model of HE Causation (adapted from Reason, 1990).

Each of the overlapping layers as seen in Figure 1 is also composed of multiple underlying causal factors of human error. These underlying causal factors allow HE to be more specifically categorized. The structure of this taxonomy can be seen in Chapter III, Figure 2. The lowest categories in this taxonomy give a thorough breakdown of the majority of the prime contributors to a human error flight mishap.

Part of the difficulty in analyzing and studying HE is developing a theory of human behavior and modeling it to human error (Park, 1994; Wickens, 1990; Senders & Moray, 1991). Analyzing and studying HE requires the development of a taxonomy using a solid theory of human performance. As described in the preceding sections, there are many taxonomies, developed by a diverse group of respected individuals, that describe HE in relation to human behavior. So where does the study of human error begin with so many HE taxonomies in the literature? To revamp or develop anew? is the question posed by Shappel and Wiegmann (1997). Researching the taxonomies from the viewpoint of the industry to be studied is the key. The answer for the U.S. Navy of

course is developing HFACS through a combination of the most relevant theories of HE to Naval Aviation.

D. SUMMARY

In spite of the academic differences in the study of human behavior, currently the mainstream view is to study behavior using the ideas of attentional and schematic control modes. The study of human behavior is essential in the development of taxonomy to study human error. From the understanding of behavior, taxonomies can be developed to chart the path and causes of HE in the operation of complex systems. Taxonomies of human error are a fundamental requirement to build a scientific foundation for the study of HE, and its causes (Hill, Byers, Rothblum & Booth, 1994). Such studies facilitate a more complete understanding of the nature, origin and causes of HE, all necessary for a clear classification scheme for describing human error. A taxonomies breakdown of the components of HE allows for the empirical study of human error.

The need for a taxonomy with which to study Naval Aviation HEs is the impetus for the development of HFACS. As stated by Shappel and Wiegmann (1997):

> Once a comprehensive model is identified, a relational database needs to be constructed to assess the interrelations among error types. A relational database would facilitate the testing of theories about the strength of the relation between latent factors and the occurrence of specific errors committed by operators. Similarly, a relational database would allow for a more refined analysis of the effects that one type of operator error (e.g., judgment error) has on the occurrence of another (e.g., procedural error). In essence, once a unifying framework is identified, the causal chain of events leading to an accident can be more easily inferred, intervention strategies more readily identified, and the tragic chain of events ultimately broken. (p. 79)

The most appropriate solution is to develop anew. The method currently used by the U.S. Navy to investigate and classify HE is a scheme that is loosely tied to a "who? what? and why?" format (Shappel & Wiegmann, 1997). This format does not allow for the structured study of HE causation. To increase the effectiveness of combating HE,

HFACS was conceived, borrowing from some of the most well developed theories of human behavior and taxonomies of human error. HFACS was developed for the U.S. Naval Aviation community to classify and to assist in the reduction and prevention of human error. HFACS is the comprehensive model of HE and a natural relational database from which to study human error. Shappel and Wiegmann envisioned HFACS would assist in the reduction of Naval Aviation FMs due to human error. HFACS provides a relational database of HE for analysts to study using statistical tools, and HFACS serves as an excellent collection device for consistent data reporting of flight mishaps. For the Naval Aviation community, the more structured and empirical study of HE through HFACS offers insight into the causes of accidents due to human error. This empirically based study of HE will lead to active policies that reduce the occurrence of Naval Aviation human errors.

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III. METHODOLOGY

The ultimate goal in this thesis is to identify human errors (HE) common to many FMs, to increase pilot awareness of these identified HE types, and eventually to reduce the overall number of flight mishaps (FMs) citing these HE types. This study uses an existing database of Class A and B Tactical Aircraft (TACAIR) Mishap Investigation Reports (MIR) maintained by the Naval Safety Center (NSC). The MIRs selected are FMs citing HE as the primary causal factor of the accident. An analysis of the HE types in the data is conducted using the Human Factors Analysis and Classification System (HFACS) taxonomy's breakdown of each flight mishap. Investigating the relationships between causal factors in the taxonomy will suggest where intervention strategies should be focused. In addition, by modeling FMs as Poisson Processes, the impact of these intervention strategies is estimated.

The analysis and impact of the intervention is complicated because HE types in the HFACS taxonomy share an involved dependence structure. The HFACS taxonomy allows a single FM to be given multiple causal factors, the causal factors or HEs are not mutually exclusive. Given that there are 17 basic types of HE labeled I,..., Y (Figure 2) with a hierarchical structure, this yields a very complex conditional framework to the HFACS taxonomy. This complicates the dependencies between causal factors to a point where basic statistical analysis and modeling becomes extremely difficult and the use of simulation techniques in conducting the analysis is more promising in obtaining a working solution. Based on original flight mishap data and a Poisson arrival process for FMs, a simulation model is built to simulate future accidents and predict the HE characteristics of these accidents. From this simulation model, the ability to estimate the expected number of accidents for a specified number of flight hours and predict specific HE types involved in the FMs is possible.

A. NAVAL SAFETY CENTER DATABASE

The NSC maintains a database, Safety Information Management System (SIMS), of all reported TACAIR flight mishaps. In 1998, Naval Aviation (NA) psychologists at the NSC took all human factors TACAIR Class A FMs from fiscal year (FY) 90 to FY98 and classified them according to the HFACS taxonomy. This classification of the Class A TACAIR FMs by the NSC is used for the analysis. The database is also queried for all Class B human factors TACAIR FMs from FY90 to FY98 to be used in the analysis. The Class B TACAIR FMs are classified according to the HFACS taxonomy by the author, using the MIRs descriptions of causal factors in the TACAIR FMs. There are 122 Class A TACAIR FMs and 19 Class B TACAIR FMs, from FY90 to FY97 that were categorized as human factors flight mishaps (FM). For FY98, there are 12 Class A TACAIR FMs and zero Class B TACAIR FMs identified as human factors flight mishaps. The data for FY98 is set aside to validate the results of the simulation model, which is built using FY90 to FY97 data.

B. MISHAP INVESTIGATION REPORTS (MIR)

MIRs contain investigative data relating to the aircraft flight mishap. They are received by the NSC in the form of message traffic and written enclosures to the MIR and are entered into the SIMS database. They contain an extensive narrative of the flight mishap and supporting information of the FM pilot and FM aircraft, and identifiable contributing FM causal factors. The MIRs for all Class A flight mishaps are quite thorough and the quality of Class B MIRs vary depending on the severity of the FM, the greater the damage the more thorough the investigation. Since the quality of Class B MIRs varied, only those FMs that were thoroughly investigated are included in the study.

C. FLIGHT MISHAP CLASSIFICATION

The Class A and B FMs that are classified according to the HFACS taxonomy are entered into a Microsoft Excel 97 spreadsheet. This creates 25 columns of binary variables, one for each type of HE (Figure 2). A "1" indicates the HE type is present in

that FM, "0" otherwise. This puts the data in a matrix that will allow an exploratory analysis to be conducted on the data using statistical computing tools, such as S-Plus©. The columns of the spreadsheet consist of categorical data including date of occurrence, aircraft type and a listing of all HFACS causal factors. Each row of the spreadsheet corresponds to individual FMs. For ease in coding, instead of using the HE nomenclature, the columns are identified using a single letter for each type of HE (Figure 2).

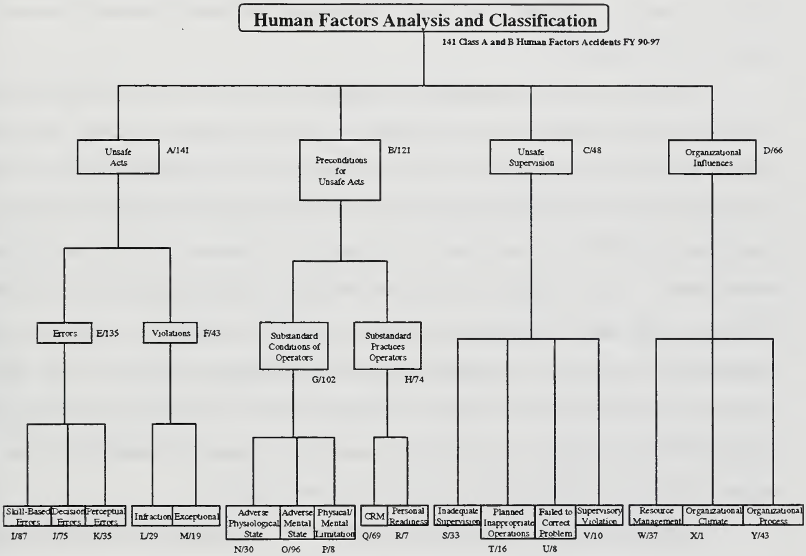

Figure 2. HFACS taxonomy: text next to the causal factor codes the factors A,..., Y and gives the number of FMs the factor is associated with. For example, A/141 codes Unsafe Acts as "A" and in 141 FMs Unsafe Acts were cited as a causal factor.

D. OVERVIEW OF ANALYSIS

Grouping HE types into levels using the hierarchical structure of the HFACS taxonomy in Figure 2 facilitates the analysis of the NA Class A and B FMs studied.

There are three basic levels in Figure 2 of the HFACS taxonomy. They are categorized in a hierarchical relationship with the lower levels being subsets of HE types contained in the higher levels. The lowest level is defined by the HE types coded I,..,Y in Figure 2 and these compose the nuclei of the HFACS taxonomy. All HE types in higher levels are composed of groupings of lower level HE types. The middle level is defined by the HE types coded E, F, G, H, C, and D in Figure 2. HE types A, B, C, and D in Figure 2 define the highest level in Figure 2. As an example of the hierarchical nature of the sets, the middle level HE type E is made up of all FMs that cited either HE type I, J, or K. Through a visual analysis of Figure 2, this hierarchical relationship discussed between HE types is readily apparent.

Statistical analysis is conducted separately for each level of the HFACS hierarchy to identify relevant causal factors and predictive patterns found in the data. The lowest level of the HFACS taxonomy will receive the majority of the analysis since the HE types contained in this level define all other levels. The correlation between the occurrence of causal factors in FMs for each level is evaluated to determine any important pairwise relationships. A cluster analysis is performed to identify important groupings of multiple HE types within each level using the function Mona in S-Plus©. A matrix of subset relationships is developed to identify important interrelations between the HE types in each level. To determine the validity of assuming a Poisson arrival process for FMs, a log linear model of the Class A and B FM occurrences is constructed using flight hour and accident data from FY90 to FY97 for Naval Aviation TACAIR.

A simulation model is developed in light of the complicated dependencies among HE types in FMs using S-Plus©. This simulation is a form of bootstrapping (see Davison & Hinkley, 1997) that sheds light on the results that classical statistics cannot. First, the simulation model generates FMs based upon a Poisson Process with arrival rate estimated from historical data. For each FM, the HE types are then generated. These are modeled directly using the empirical distribution of the historical HE type combinations. This distribution is composed of all Class A and B TACAIR FMs from FY90 to FY97 and is seen as fair representation of the distribution of HE types found in Naval Aviation

TACAIR flight mishaps. Potential intervention strategies are identified based on the simulation results and are compared to FY98 flight mishaps.

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IV. RESULTS

The purpose of the data analysis is to determine important relationships between the 25 causal factors in the Human Factors Analysis and Classification System (HFACS) taxonomy (A – Y of Figure 2) and verify that the accident arrivals for the Class A and B Tactical Aircraft (TACAIR) Human Error (HE) Flight Mishaps (FMs) can be modeled as a Poisson Process. The data used for the analysis are the 141 Class A and B TACAIR FMs between fiscal year (FY) 90 and FY97 that cited HE as the primary causal factor (FMs due entirely to mechanical or maintenance human factors were excluded). The TACAIR FMs for FY98 are set aside to validate the flight mishap (FM) rate of the model.

A. DATA ANALYSIS OF CAUSAL FACTORS

Classifying the 141 FMs according to the HFACS taxonomy (Figure 2) gives a binary row vector of 1's and 0's for each flight mishap. A "1" indicates that causal factor is cited in the FM, a "0" indicates that causal factor is not cited in the flight mishap. Combining these vectors gives a 141x25 binary asymmetric matrix X with FMs defining the rows and the HE types defining the columns. In addition, we define sets for analysis corresponding to each causal factor to be subsets of FMs that cited that causal factor (Table 1). Exploration of the data is undertaken by analyzing the relationship between these sets.

1. Notation and Structure Data

For initial data exploration, the HE types correspond to sets of FMs that exhibit that HE as defined in Table 1. The relationships between the sets are defined as:

$$(A \cup B \cup C \cup D) = XX, \tag{1}$$

$$(E \cup F) = A, \tag{2}$$

$$(G \cup H) = B, \tag{3}$$

$$(S \cup T \cup U \cup V) = C, \tag{4}$$

$$(W \cup X \cup Y) = D, \tag{5}$$

$$(I \cup J \cup K) = E, \tag{6}$$

$$(L \cup M) = F, \tag{7}$$

$$(N \cup O \cup P) = G, \tag{8}$$

$$(Q \cup R) = H. \tag{9}$$

Note that sets on the left-hand side of equations (1) to (9) are not necessarily mutually exclusive. There is a hierarchical relationship between these sets as shown in set equations (1) to (9) and visually in Figure 2. This relationship is used to infer findings in the lowest level to higher level HE types, which is important because it allows the study to focus on the most basic HE types. The corresponding HE types at the bottom of the HFACS in Figure 2 are exhaustive in their classification of error. They are considered subsets of the HE types defined in the higher levels. For example, see equation (9), HE type E (Error) contains all FMs that cited either HE type I (Skill-Based Error), J (Decision Error) or K (Perceptual Error) or any combination of the three.

Three classes of sets are constructed using this subset relationship. Each class represents a level of classification in the HFACS hierarchy. The first class HFACSA is built from the top level (Figure 2), sets A, B, C and D (Table 1), the second class HFACSB is built from the middle level (Figure 2), sets E, F, G, H, C and D (Table 1), and the third class HFACSC is built from the bottom level (Figure 2), sets I,...,Y (Table 1). Appendix E contains a key for HE types coding.

Table 1. Set definitions for HFACS sets A...Y and the Universal set XX. Example: set A contains all FMs that identified A as a causal factor.

Set Definitions:		
XX	=	{all TACAIR human factors Class A & B FMs from FY90 to FY97, excluding excluding those FMs attributable to mechanical or maintenance human factors}
A	=	{xx | xx cited as a causal factor Unsafe Acts}
B	=	{xx | xx cited as a causal factor Preconditions for Unsafe Acts}
C	=	{xx | xx cited as a causal factor Unsafe Supervision}
D	=	{xx | xx cited as a causal factor Organizational Influences}
E	=	{xx | xx cited as a causal factor Errors}
F	=	{xx | xx cited as a causal factor Violations}
G	=	{xx | xx cited as a causal factor Substandard Conditions of Operators}
H	=	{xx | xx cited as a causal factor Substandard Practices of Operators}
I	=	{xx | xx cited as a causal factor Skill-Based Errors}
J	=	{xx | xx cited as a causal factor Decision Errors}
K	=	{xx | xx cited as a causal factor Perceptual Errors}
L	=	{xx | xx cited as a causal factor Infraction}
M	=	{xx | xx cited as a causal factor Exceptional}
N	=	{xx | xx cited as a causal factor Adverse Physiological State}
O	=	{xx | xx cited as a causal factor Adverse Mental State}
P	=	{xx | xx cited as a causal factor Physical/Mental Limitation}
Q	=	{xx | xx cited as a causal factor Crew Resource Management (CRM)}
R	=	{xx | xx cited as a causal factor Personal Readiness}
S	=	{xx | xx cited as a causal factor Inadequate Supervision}
T	=	{xx | xx cited as a causal factor Planned Inappropriate Operations}
U	=	{xx | xx cited as a causal factor Failed to Correct Problem}
V	=	{xx | xx cited as a causal factor Supervisory Violation}
W	=	{xx | xx cited as a causal factor Resource Management}
X	=	{xx | xx cited as a causal factor Organizational Climate}
Y	=	{xx | xx cited as a causal factor Organizational Process}

Another way to look at these classes is by identifying them with the matrix X defined at the beginning of Chapter IV. X is a 141x25 matrix with all HFACS HE types defining the columns and all 141 FMs between FY90 and FY97 defining the rows. The first class corresponds to the four columns of X, which are indicators for sets A, B, C and D. Extracting these four columns from X gives a 141x4 matrix that is equivalent to the first class; these four column vectors define the matrix X_A. The second class corresponds to column vectors E, F, G, H, C and D of X. Extracting these six columns from X gives a 141x6 matrix that is equivalent to the second class; these six column vectors define the matrix X_B. The third set corresponds to column vectors I,...,Y of X. Extracting these 17

columns from X gives a 141x17 matrix that is equivalent to the third class; these 17 column vectors define the matrix X_C. All FMs contained in classes HFACSA, HFACSB and HFACSC are also contained in their respective matrices X_A, X_B and X_C along with the corresponding FM causal factors. Looking at the classes and the matrices one should again note that none of the sets is mutually exclusive, a single FM may belong to many different sets. For this reason, there are multiple dependent relationships among the HE types. Analysis using the simple probability of a HE types occurrence cannot be used in the exploration of relationships in the HFACS taxonomy.

2. Analysis of Pairwise Dependency

To take an initial look at the relationship between HE types, correlation matrices are calculated for the columns of X_A, X_B and X_C (Appendix A). The highest correlation for all three matrices is in X_C between set N (Adverse Physiological State) and K (Perceptual Errors) with a correlation of .623. After this, the highest correlation is .409 between sets U (Failed to Correct Problem) and V (Supervisory Violation) in the matrix X_C. All correlations otherwise range between -.287 and .344 for all three matrices. The accident data is examined and the relationship between N and K is found to have a mild positive relationship. In addition, U and V are found to have an even milder positive relationship. The correlation between N and K addresses 23 FMs (Table 2), and the correlation between U and V only addresses 4 flight mishaps. The fact that the only potentially important relationships in the correlations are found in X_C is not surprising given the hierarchical nature of the HFACS taxonomy. Since the upper levels of the HFACS taxonomy are defined by lower level sets, the correlations are diminished in significance as one proceeds up the classifications in the taxonomy.

From this point on, this analysis will concentrate on the class HFACSC. The reason for concentrating on HFACSC is that the HE types defining this class are the most substantive HE types. They are an exhaustive listing of HE types that are used to define the sets in the higher classes of the HFACS taxonomy. The intent of further study is to concentrate on the more specific HE types of HFACSC. This can be done without loss of

generality since all sets in the class HFACSC are subsets of sets in both classes HFACSB and HFACSA as defined in set equations (1) – (9).

To look more closely at HFACSC, we first compute a matrix that defines the number of FMs that cite a specific HE type and the combinations of HE types (Table 2),

$$M_C = (X_C)^T (X_C). \tag{10}$$

The rows and columns of M_C are indexed by i, j = I,...,Y, let each $m_c(i,j)$ be the number of FMs in the intersection of sets i and j. Then $m_c(i,i)$ defines the number of FMs contained in set i. As an example, $m_c(N,K) = 23$, is the number of FMs in the intersection of sets N and K, so 23 FMs between FY90 and FY97 cited both HE type N and K as causal factors in the FM.

To calculate the proportions, FMs in pairwise intersections of HEs, let P_C be the proportion matrix,

$$P_C = m_c(i,j)/141 \qquad \forall i,j, \tag{11}$$

where 141 is the total number of FMs in FY90 to FY98. The diagonal of this matrix gives P(i), the proportion of total FMs citing HE type "i" to the total number of FMs studied (Table 3). All other cells give P (i ∩ j), the proportion of total FMs citing HE type "i" and "j" in combination to the total number of FMs studied (Table 3). A notable observation in the analysis is that proportion $P_C(i,i)$ or the proportion of FMs with HE i is not the sum of $P_C(i,j)$ for all j, because of the non-mutually exclusive character of HFACS.

Table 2. Matrix M_C (Intersection of Sets). Example, at cell $m_c(I,J)$, the intersection of sets I and J indicates that 38 of 141 FMs between FY90 and FY97 shared the causal factor combination of I and J. At cell $m_c(I,I)$ there are 87 FMs indicating that HE type I was cited as a causal factor in 87 of 141 FMs between FY90 and FY97.

	I	J	K	L	M	N	O	P	Q	R	S	T	U	V	W	X	Y
I	87	38	16	14	5	18	65	6	44	4	19	9	6	9	24	1	25
J		75	12	16	11	11	51	1	45	3	20	12	6	7	18	0	27
K			35	12	7	23	28	2	15	4	8	3	3	2	9	1	7
L				29	5	9	17	1	12	2	7	1	4	3	5	1	7
M					19	5	9	2	9	2	2	2	1	0	3	1	2
N						30	25	2	12	3	7	2	3	2	9	1	8
O							96	7	49	6	23	14	8	9	27	1	30
P								8	5	1	1	0	1	1	3	0	2
Q									69	2	15	7	4	5	14	1	20
R										7	4	1	1	1	0	0	2
S											33	8	3	5	8	0	12
T												16	0	1	4	0	6
U													8	4	3	1	2
V														10	4	0	3
W															37	0	15
X																1	0
Y																	43

Table 3. The proportion matrix P_C, the diagonal of this matrix gives the $P(i)$ and all other cells give the $P(i \cap j)$ for all i and j.

	I	J	K	L	M	N	O	P	Q	R	S	T	U	V	W	X	Y
I	0.62	0.27	0.11	0.10	0.04	0.13	0.46	0.04	0.31	0.03	0.13	0.06	0.04	0.06	0.17	0.01	0.18
J		0.53	0.09	0.11	0.08	0.08	0.36	0.01	0.32	0.02	0.14	0.09	0.04	0.05	0.13	0.00	0.19
K			0.25	0.09	0.05	0.16	0.20	0.01	0.11	0.03	0.06	0.02	0.02	0.01	0.06	0.01	0.05
L				0.21	0.04	0.06	0.12	0.01	0.09	0.01	0.05	0.01	0.03	0.02	0.04	0.01	0.05
M					0.13	0.04	0.06	0.01	0.06	0.01	0.01	0.01	0.01	0.00	0.02	0.01	0.01
N						0.21	0.18	0.01	0.09	0.02	0.05	0.01	0.02	0.01	0.06	0.01	0.06
O							0.68	0.05	0.35	0.04	0.16	0.10	0.06	0.06	0.19	0.01	0.21
P								0.06	0.04	0.01	0.01	0.00	0.01	0.01	0.02	0.00	0.01
Q									0.49	0.01	0.11	0.05	0.03	0.04	0.10	0.01	0.14
R										0.05	0.03	0.01	0.01	0.01	0.00	0.00	0.01
S											0.23	0.06	0.02	0.04	0.06	0.00	0.09
T												0.11	0.00	0.01	0.03	0.00	0.04
U													0.06	0.03	0.02	0.01	0.01
V														0.07	0.03	0.00	0.02
W															0.26	0.00	0.11
X																0.01	0.00
Y																	0.30

An important part of this analysis is looking at the conditional proportions of FMs in the intersection of HE sets. To determine these conditional proportions, let S_C be the matrix,

$$S_C = m_c(i,j)/\, m_c(i,i) \qquad \forall i,j. \tag{12}$$

The entries of S_C give the proportion of FMs citing a specific causal factor given that FM also cites another causal factor (Table 4). For example, at cell (O, T), (read column to row) (.88 x 100) percent of the time given an FM cites HE type T (Planned Inappropriate Operations) as a causal factor, that FM will also cite HE type O (Adverse Mental State) as a causal factor.

Table 4. The subset matrix S_C. Example, at cell (O, T), (in order to read the relationship correctly, read the column causal factor first. Then read the row causal factor in the following statement) when HE type T is cited in an accident, (.88 x 100) percent of the time HE type O is also cited in that mishap.

	I	J	K	L	M	N	O	P	Q	R	S	T	U	V	W	X	Y
I		0.51	0.46	0.48	0.26	0.60	0.68	**0.75**	0.64	0.57	0.58	0.56	**0.75**	**0.90**	0.65	1.00	0.58
J	0.44		0.34	0.55	0.58	0.37	0.53	0.13	0.65	0.43	0.61	**0.75**	**0.75**	**0.70**	0.49	0.00	0.63
K	0.18	0.16		0.41	0.37	**0.77**	0.29	0.25	0.22	0.57	0.24	0.19	0.38	0.20	0.24	1.00	0.16
L	0.16	0.21	0.34		0.26	0.30	0.18	0.13	0.17	0.29	0.21	0.06	0.50	0.30	0.14	1.00	0.16
M	0.06	0.15	0.20	0.17		0.17	0.09	0.25	0.13	0.29	0.06	0.13	0.13	0.00	0.08	1.00	0.05
N	0.21	0.15	0.66	0.31	0.26		0.26	0.25	0.17	0.43	0.21	0.13	0.38	0.20	0.24	1.00	0.19
O	**0.75**	0.68	**0.80**	0.59	0.47	**0.83**		**0.88**	**0.71**	**0.86**	**0.70**	**0.88**	**1.00**	**0.90**	**0.73**	1.00	**0.70**
P	0.07	0.01	0.06	0.03	0.11	0.07	0.07		0.07	0.14	0.03	0.00	0.13	0.10	0.08	0.00	0.05
Q	0.51	0.60	0.43	0.41	0.47	0.40	0.51	0.63		0.29	0.45	0.44	0.50	0.50	0.38	1.00	0.47
R	0.05	0.04	0.11	0.07	0.11	0.10	0.06	0.13	0.03		0.12	0.06	0.13	0.10	0.00	0.00	0.05
S	0.22	0.27	0.23	0.24	0.11	0.23	0.24	0.13	0.22	0.57		0.50	0.38	0.50	0.22	0.00	0.28
T	0.10	0.16	0.09	0.03	0.11	0.07	0.15	0.00	0.10	0.14	0.24		0.00	0.10	0.11	0.00	0.14
U	0.07	0.08	0.09	0.14	0.05	0.10	0.08	0.13	0.06	0.14	0.09	0.00		0.40	0.08	1.00	0.05
V	0.10	0.09	0.06	0.10	0.00	0.07	0.09	0.13	0.07	0.14	0.15	0.06	0.50		0.11	0.00	0.07
W	0.28	0.24	0.26	0.17	0.16	0.30	0.28	0.38	0.20	0.00	0.24	0.25	0.38	0.40		0.00	0.35
X	0.01	0.00	0.03	0.03	0.05	0.03	0.01	0.00	0.01	0.00	0.00	0.00	0.13	0.00	0.00		0.00
Y	0.29	0.36	0.20	0.24	0.11	0.27	0.31	0.25	0.29	0.29	0.36	0.38	0.25	0.30	0.41	0.00	

For purposes of identifying important conditional proportions in the matrix in Table 4, a floor of (.70x100) percent is set for that case to be considered in further analysis. There are 19 such sets which meet the 70 percent floor in Table 4 (entries in the X column are not considered since they represent only one FM and do not provide any insight into other flight mishaps). These sets are listed in Table 5. The most important

combinations contain HE type O (Adverse Mental State) the largest proportion of the time, 12 of 19 times in Table 5. The most important combinations after these are I (Skill-Based Error) 3 of 19 and J (Decision Error) 3 of 19. Clearly, Adverse Mental State stands out as a consequential factor in Table 4.

To explore these stronger relationships found in the analysis and listed in Table 5, a simulation model is constructed to predict the character and occurrence of future HE in Naval Aviation TACAIR Class A and B flight mishaps. By using historical FM data, we can simulate the conditional proportion of HE types and then construct confidence intervals (CIs) based on the simulated occurrence of the HE types, to determine their statistical significance.

Table 5. Important Subsets in Table 4. For example: $P \subset O$, 87.5 percent of all accidents citing causal factor P also cited causal factor O.

Relationships	Percentage
$U \subset O$	100.0
$P \subset O$	87.5
$T \subset O$	87.5
$R \subset O$	85.7
$V \subset O$	81.8
$V \subset I$	81.8
$N \subset O$	80.6
$K \subset O$	78.3
$N \subset K$	77.4
$P \subset I$	75.0
$T \subset J$	75.0
$U \subset I$	75.0
$U \subset J$	75.0
$I \subset O$	73.8
$V \subset J$	72.7
$S \subset O$	70.5
$Q \subset O$	70.4
$Y \subset O$	70.0
$W \subset O$	70.0

3. Cluster Analysis

Cluster analysis of the data is accomplished using a monothetic clustering method for analysis of matrices with asymmetric binary variables (Kaufman & Rousseeuw, 1990). This method takes advantage of the binary asymmetric structure of the HFACS matrices. The method clusters the data according to its combination of 1's and 0's. This method is applied to all three sets using the function mona in S-Plus© with the following results:

1) HFACSA with four sets has 2^4 combinations and it clustered into eight separate combinations.

2) HFACSB with six sets has 2^6 combinations and it clustered into 32 separate combinations.

3) HFACSC with 17 sets has 2^{17} combinations and it clustered into 121 separate combinations.

The 121 combinations used by Mona to cluster HFACSC covered 141 accidents, 13 combinations shared multiple accidents, while 108 accidents are unique combinations (see Table 6 for listing of multiple accidents sharing the same causal factor combinations).

Within the cluster analysis of all 141 accidents, certain combinations appear dominant, as can be partially seen in Table 6 and are fully listed in Table 7 for the 121 separate combinations found in the cluster analysis. It can be seen that O (Adverse Mental State) and Q (CRM) appear in combination with other causal factors a large proportion of the time. Of the 17 causal factors, there are four factors which reoccur repeatedly in all accident combinations, these are O (Adverse Mental State), Q (Crew Resource Management (CRM)), I (Skill-Based Errors), and J (Decision Errors). This pattern can also be seen in an analysis of pairwise dependency in the sets, where O (Adverse Mental State) was identified as the most important factor in the analysis. It can be seen in Table 7 that Adverse Mental State is also contained in 6 of the 9 important combinations identified in the cluster analysis. This agreement in each analysis as to the

importance of Adverse Mental State highlights the significance of HE type O (Adverse Mental State) in Naval Aviation TACAIR flight mishaps.

Table 6. Combinations of causal factors which are common to more than one accident. Example, three accidents share the same causal factor combination of I and Q.

Accidents	Combinations of Causal Factors
Two	I
	I, O, W, Y
	I, O, Q
	I, O, Q, W
	I, J, Q, Y
	I, J, O, Q, Y
	I, J, L, O, Q
	I, K, N, O, Q
	J, Q
	J, O
Three	I, Q
Four	I, O
Five	I, J, O, Q

Table 7. Percent of accidents having the specific causal factor combinations. Example, for the combination O & J (Adverse Mental State and Decision Error) 50 percent of all accidents studied had both of these listed as causal factors in the accident.

Combinations.	Percent of Accidents
O & I	50%
O & J	40%
O & Q	39%
O & K	21%
O & Y	24%
O & W	21%
I & J	29%
Q & J	35%
Q & I	32%

B. ANALYSIS OF ACCIDENT ARRIVAL RATES

A general log linear regression model that hypothesizes a Poisson distribution with rate proportional to flight hours supports the assumption that the accident arrival rate follows a Poisson Process. Data used to construct the log linear regression model are flight hours for Naval TACAIR for FY90 to FY97 and the number of Class A and B

TACAIR FMs for FY90 – FY97 (Table 8). The regression model uses the expected value of a Poisson arrival process to test the hypothesis that the data is from a Poisson distribution with,

$$E(\text{TACAIR FMs}) = \lambda t, \tag{13}$$

where λ is the accident arrival rate/100,000 flight hours and t is flight hours per year/100,000. Taking the natural log (ln) of both sides yields a log linear equation for regression,

$$\ln[E(\text{TACAIR FMs})] = \ln(\lambda) + \ln(t). \tag{14}$$

Restating equation (14) using regression coefficients and variables, gives the following equation:

$$\ln[E(\text{TACAIR FMs})] = \beta_0 + \beta_1 x_1, \tag{15}$$

where $\beta_0 = \ln(\lambda)$, β_1 is the regression coefficient for x_1 and $x_1 = \ln(t)$.

If equation (15) is considered representative of a Poisson process, then β_1 must equal one. To test the hypothesis, H_0: $\beta_1 = 1$, the data in Table 8 is fit to a log linear model (equation (15)). Using S-Plus© to calculate the coefficients and variables of the log linear regression model, a 95 percent confidence interval (CI) of (.6527, 3.014) is found for β_1. Since 1 is contained in the 95 percent CI, at an $\alpha = .05$, the hypothesis that $\beta_1 = 1$ cannot be rejected and the distribution is assumed to be Poisson with the rate proportional to flight hours.

Table 8. Flight Hours and Human Factors Class A and B TACAIR FMs FY90 to FY98.

Fiscal Year	Flight Hours	Class A and B TACAIR Human Factors FMs
90	633,228	26
91	660,314	23
92	597,393	15
93	577,133	23
94	522,700	9
95	503,559	16
96	479,577	18
97	421,150	11
98	406,777	12

C. SIMULATION

The simulation is built using S-Plus© (see Appendix C for simulation code) with two principle assumptions:

1) That accident arrivals can be modeled using a Poisson Process.
2) All HE types for future FMs can be modeled from the 121 distinct accident combinations found in the Monothetic cluster analysis (Mona).

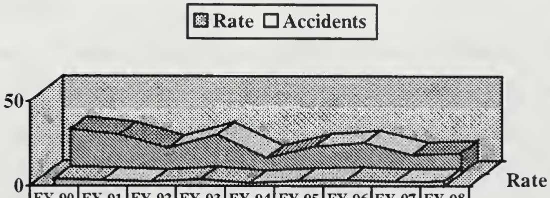
To run a simulation, the average accident arrival rate from FY90 to FY97 is used along with FY98 flight hours/100,000 (Table 8) to generate accidents from a Poisson distribution, where the average accident arrival rate is assumed to be the sum of the flight hours/100,000 from FY90 to FY97 divided by the sum of the Class A and B TACAIR FMs from FY90 to FY97 (Figure 3). Each iteration generates an observation from the Poisson distribution; this sets the number of accidents for that simulated period. In a simulation there are 1000 iterations, each iteration representing one time period with its own specific number of flight mishaps.

The characteristics of individual accidents for each period are determined by a uniform random selection between 1 and 141 (the total number of TACAIR Class A and B FMs FY90 – FY97), the FM characteristics based on the 141 historical HE types found in FY90 to FY97 flight mishaps. This is equivalent to a nonparametric sampling bootstrap with replacement from the empirical distribution of historical FM characteristics. This allows for formal inference.

Based on the Naval Aviation TACAIR Class A and B FM rate from FY90 to FY97, the accident arrival rate is 3.21 FMs/100,000 flight hours. Using the Class A and B TACAIR flight mishap rate, the simulation model can be validated with FY98 flight hours. To compute the distribution of FMs predicted for FY98, use the accident arrival rate for FY90 to FY97 and the flight hours flown in FY98 and run it through two thousand iterations in the simulation model. Using 408,500 flight hours flown for FY98,

the results of the simulation are an expected value of 13 FMs in FY98, the actual accident rate for FY98 is 12 flight mishaps.

Accidents and Accident Rate FY90 - FY98



	FY-90	FY-91	FY-92	FY-93	FY-94	FY-95	FY-96	FY-97	FY-98
Rate	4.106	3.483	2.511	3.985	1.722	3.177	3.753	2.612	2.95
Accidents	26	23	15	23	9	16	18	11	12

Figure 3. Class A and B TACAIR average accident arrival rate/100,000 flight hours from FY90 to FY98.

The frequency of important HE types, found to be important both singularly and in combination (Table 5) in earlier analysis, is calculated for the simulation run. Important singular HE types are considered from earlier analysis to be Adverse Mental State, Skill Based Errors, Decision Errors, Crew Resource Management and Organizational Process, each of these has a proportion of occurrence greater than .30 (Table 4).

For the simulation run of 1000 iterations, Figure 4 displays the histogram of the accident arrival rate. The mean and 95 percent CIs for each HE type both individually and in combination (Table 5) are computed and listed in Appendix B. For a HE type either individually or in combination (Table 5) to be considered significant, it is hypothesized that at $\alpha = .05$ the expected number of FMs predicted is greater than 0. All single HE types that are considered important and run in the simulation are found to be significant at $\alpha = .05$. For the important combinations in Table 5 only I (Skill-Based Error) – O (Adverse Mental State) and Q (CRM) – O (Adverse Mental State) are significant at $\alpha = .05$.

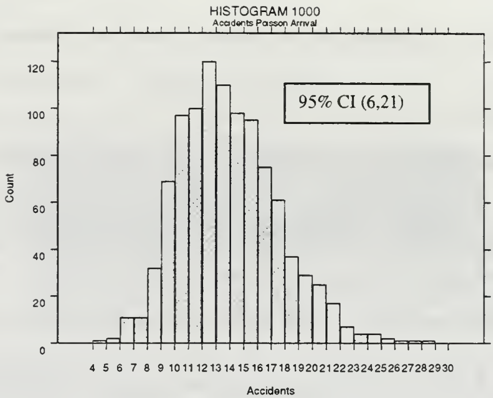


Figure 4. Histogram of 1000 iterations of simulation, showing the wide variance of the number of accidents yielded by the Poisson arrival rate for Class A and B TACAIR FMs.

The results in the simulation support the importance of the HE type O (Adverse Mental State), exhibited in both the cluster analysis and the pairwise dependency analysis. The most substantial support from the simulation is found in the pairwise combinations, where Adverse Mental State is in 2 of 2 combinations, the only significant combinations that are found in the simulation. Adverse Mental State is significant in all three separate types of analysis, emphasizing the importance of Adverse Mental State in TACAIR human error flight mishaps between FY90 and FY97. Notably, there are no other HE types that influenced the analysis as strongly as Adverse Mental State.

V. SUMMARY, DISCUSSION AND RECOMMENDATIONS

A. SUMMARY

The study of human error (HE) in Naval Aviation (NA) flight mishaps (FM) does not often present a clear path to a single primary causal factor. Accidents, which occur primarily due to HE, are often composed of a web of intertwined factors that contribute to the accident. The recently developed Naval Safety Center (NSC) Human Factors Analysis and Classification System (HFACS) assists in explicating the picture. Through research and studies, Naval Aviation psychologists at the NSC have taken approximately 289 HE classifications (Shappel & Wiegmann, 1994) and clustered them into 25 basic distinct HE types (Figure 2). Each of these 25 separate categories is a node on this web of intertwined causal factors. These nodes are composed of multiple types of human failures grouped together because of their similarities. Within each of these nodes is a web of its own which may appear clear and symmetric for analysis of any particular FM or may be tangled and chaotic in the analysis of the flight mishap.

Whether a FM is clear or tangled, the power in the HFACS taxonomy is that it allows the researcher to classify many single HEs into specific groupings, allowing for a focused analysis. For example, Adverse Mental State in the HFACS taxonomy is composed of approximately ten individual types of human error. These individual types of HE are grouped under a common idea, the pilot is not mentally prepared for the flight and this adversely affects the pilot's performance. Breaking the taxonomy into 25 basic HE categories allows the researcher to concentrate on specific general types of HE. Instead of having to study 289 separate types of HE, the researcher can focus on 25 clusters of general HE causation. This clustering of HE by HFACS and its foundation in widely accepted theories of HE allows a well-structured analysis of human factors flight mishaps.

In this analysis of 141 Class A and B TACAIR human factors FMs, the design of the HFACS taxonomy allows one to focus on specific intervention strategies. The key to the analysis is the subset relationships, equations (1) to (9). The 289 types of HE are clustered in 17 categories of general HE types, the bottom row of Figure 2. To analyze the relationships between these 17 sets I, ...,Y (Table 1), the matrix of subsets is studied (Table 4). This matrix presents an important relationship in Adverse Mental State (Table 3), for 12 of the 17 HE sets primarily contained in Adverse Mental State. The next closest relationship looking at subsets is Skill Based Error and Decision Error, each of these substantially encompassed three HE sets. All other relationships within the subset matrix showed no important patterns.

The important pattern seen in the relationships between Adverse Mental State and the 12 other causal factors definitely stands out among all other relationships considered. Nowhere else in the data is such an important relationship found. So the questions arise, do we need to look at causal factors having important relationships with other causal factors, or should we concentrate on the most frequently occurring singular causal factors? According to some theorists, all that is required to prevent an accident is intervention at a single level or causal factor and the FM could be prevented. This may be a start to prevention but some would consider this theory a bit simplistic (Zotov, 1996).

An FM is composed of many HEs, and even though these single HEs are clustered into common categories of error, there is a great deal of entanglement between categories. It is constructive to picture the HE entanglement as a circular web of dominos connected by multiple strands of a spider's web. If one causal factor to a flight mishap is removed, there is no guarantee that the chain of events leading to the FM has been severed. Just as in a spider's web, removing one segment of the web doesn't guarantee that the web has been destroyed. The study of HE is not an exact science, and it is often clouded by many variables in its study. For this reason, the focus cannot be singular, but one must try to encompass as many factors as possible. In attempting to reduce the FM rate, the focus cannot be on a singular cause that seems to stand alone in the analysis. The focus needs

to be on an HE type that appears to be an important member of this total FM web (Figure 5).

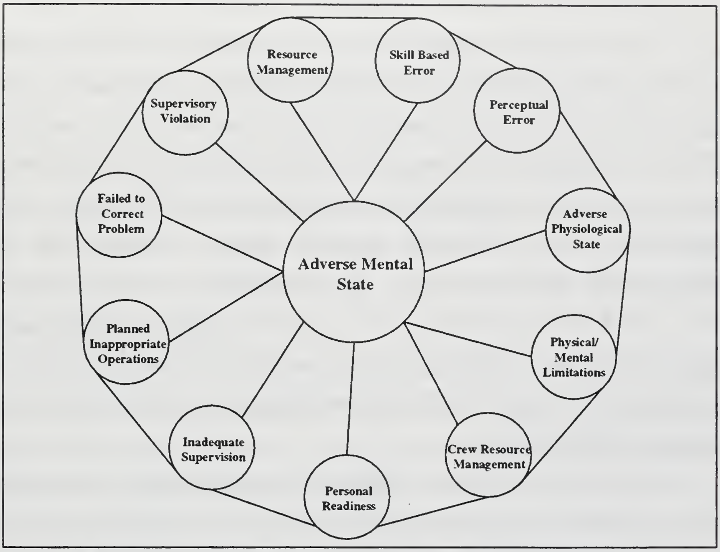


Figure 5. Web of Important Relationships Surrounding Adverse Mental State.

The important factor for this study in the FM web is Adverse Mental State, as stated previously, 12 of the 17 bottom HE types in the HFACS taxonomy have important subset relationships within Adverse Mental State. These 12 important factors are: Skill-Based Errors, Perceptual Errors, Adverse Physiological State, Physical/Mental Limitations, Crew Resource Management, Personal Readiness, Inadequate Supervision, Planned Inappropriate Operations, Failed to Correct Problem, Supervisory Violations, Resource Management, and Organizational Process. As seen in Figure 5, these HE types create an FM web, where Adverse Mental State connects to each factor in an important way. If intervention at the point of Adverse Mental Error were attempted, this intervention would affect many other possible causal factors in a potential FM. Listed in

Appendix F is a detailed description of the HFACS taxonomy, and it describes the 12 general types of HE categories attached to Adverse Mental State (Figure 5).

B. DISCUSSION

In a recent message released by the NSC (Aviation Safety Monthly Summary for Feb. '99), the NSC highlighted NA's current progress in reducing HE. The message looked at Class A FMs for all NA aircraft between fiscal years (FY) 90 and FY98, a total of 212 FMs. Analyzing the findings of the NSC's message gives a comparison with this current study of Naval TACAIR Class A and B FMs from FY90 to FY97. This gives a comparison of how the TACAIR community is doing compared with the NSC's impression of the NA fleet as a whole. To recap the thesis, it covered all Naval TACAIR Class A and B FMs from FY90 to FY97, and FY98 is used to validate the simulation model used in the study. Of the total 212 Class A FMs evaluated in the NSC's message, this thesis looks at 134 of these FMs (63 percent) and an additional 19 Class B FMs are included for FY90 to FY98.

The following discussion contrasts the three main points presented in the NSC message with the findings of this thesis. To begin, let us first review the NSC's points:

1) For all Class A Naval Aircraft FMs from FY90 to FY98 a downward trend in the FM rate exists.

2) A strong correlation between leadership and the reduction of violations exists.

3) In FY98, "Skill-Based Errors" emerged unchecked and the current trend shows that this type of HE will be involved in an excess of 65 percent of future FMs.

The above statements regarding Naval Aviation in general from FY90 to FY98 are insightful points of contrast to compare this analysis of Naval Aviation TACAIR. Take the first point concerning the downward trend in Naval Aviation's FM rate from FY90 to FY98. An initial observation of the TACAIR data and NA in general is that discerning a downward trend in the Naval Aviation FM rate is difficult. The reason for this is that the

accident arrival rate is assumed to be best modeled by a Poisson arrival process, and it is difficult to determine a trend when moving from one year to the next. This is especially true when the arrival rate does not deviate far from the mean of the assumed distribution.

In a Poisson arrival process, the number of FMs are expected to fluctuate above and below the mean, so care must be taken when trying to identify trends. We must be careful when stating that a downward trend exists because of the randomness found in the occurrence of human error. The actual FY98 FM rate for Naval TACAIR is one accident below the expected eight-year average arrival rate of the simulation run. Therefore, it cannot be concluded that there has been a statistically significant change in the true flight mishap rate (Figure 4). Looking at the data for FY90 to FY98, neither can it be concluded that there is a downward trend in the FM rate for the Naval TACAIR community during this period.

The second issue to contrast is the reduction in violations due to better leadership and supervision in the NA community. Looking at the Naval TACAIR community's human error FMs from FY90 to FY97, refer to the correlation matrices (Appendix C) to find that the correlation between Unsafe Supervision (C) and Violations (F) is –0.076. This correlation suggests that in Naval TACAIR there is no positive relationship between the findings of "Unsafe Supervision and Violations" in the TACAIR human factors FMs studied. If "Unsafe Supervision" is cited in an accident, then the chance that "Violation" is cited in the accident does not increase and vice versa. Therefore, during the period FY90 to FY97, there was no significant positive relationship between "Unsafe Supervision and Violations" in the Naval TACAIR community. Any finding regarding this relationship during the period FY90 to FY97 would have to be drawn from sources other than the HFACS categorization of HE that are based on the MIRs.

The third point to contrast is the rise of "Skill-Based Error" in NA. To look at this problem in Naval TACAIR, a spreadsheet is constructed with the following attributes: 25 columns each containing a causal factor in the HFACS taxonomy and 9 rows for FY90 to FY98. The data for FY98 is sparse because not all FMs have been closed out and released for analysis. Each cell contains the total number of accidents that

cited a specific causal factor for that fiscal year. The cells were then divided by the total TACAIR flight hours for that fiscal year and multiplied by 100,000 (Appendix D). This allows all cells to be compared on the same scale, the number of causal factors/100,000 flight hours. Upon inspecting the "Skill-Based Error" rates from FY90 to FY98, no important fluctuations are found. Looking at Figure 6, a histogram of the FY98 simulation run results for "Skill-Based Error," if all twelve accidents considered in this study for FY98 should cite "Skill-Based Error" as a causal factor in the FM. Nothing can be concluded about this event being statistically significant because the twelve accidents are contained in the 95 percent CI for the "Skill-Based Error" distribution, calculated using the simulation.

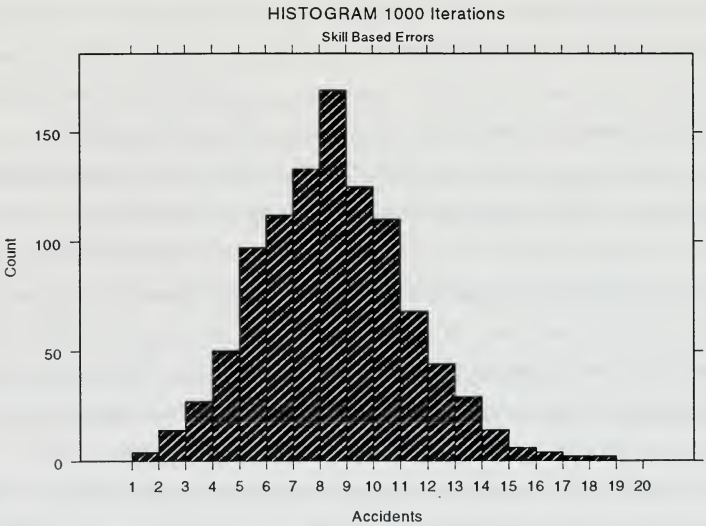


Figure 6. Poisson distribution of "Skill-Based Errors", based on 408,500 flight hours, using simulation model n=141.

C. RECOMMENDATIONS

The Naval TACAIR communities flight mishap rate has remained fairly constant from FY90 to FY97 and given the assumption of a Poisson arrival rate for FMs, the FY98 FM rate has been well modeled. The actual accident rate in FY98 is 12 TACAIR flight mishaps that are attributable to HE and the model predicts 13 FMs due to HE for FY98. The models 95 percent confidence interval (CI) for the FY98 expected accident rate is (6,21), the actual FM rate of 12 is well contained in the 95 percent CI. The conclusion from the model's result is that there has been no significant change in Naval TACAIR's human factors FM rate in FY98 when compared to the long-term FM rate from FY90 to FY97.

Looking at the results from the simulation (Appendix B), there are five significant singular causal factors: "Adverse Mental State, Skill-Based Errors, Decision Errors, Crew Resource Management and Organizational Process." These five causal factors all had the highest probability of occurrence when compared with other causal factors. Looking at combinations of causal factors (Appendix B) only two significant combinations, "Adverse Mental State and Skill-Based Errors" and "Adverse Mental State and Crew Resource Management" exist. There are two recommendations for intervention that are discussed in the following paragraphs, each from a different point of view for HE intervention.

If the viewpoint of removing a single causal factor (the Domino theory) is the basis of the recommendation, then there would be five points of intervention: "Adverse Mental State, Skill-Based Errors, Decision Errors, and Organizational Process." In the case of "Crew Resource Management," the NSC has already developed a program for NA to increase the awareness of "Crew Resource Managements" importance in NA. Taking the other four causal factors, the expected mean value for accidents/100,000 flight hours are listed in Table 9 along with a 50 percent intervention FM reduction for discussion.

Table 9. Mean accidents/100,000 flight hours predicted in simulation for significant single causal factors. Example: it is predicted that 2.179 FMs/100,000 flight hours will cite Adverse Mental State as a causal factor.

	Mean/100,000 flight hours	50% reduction
Adverse Mental State	2.179	1.090
Skill-Based Error	1.950	0.975
Decision Error	1.768	0.884
Organizational Process	0.997	0.499

Looking at Adverse Mental State in Table 9, as an example, the Navy should develop a program to intervene and educate aviators to the hazards of Adverse Mental State. If the program were 50 percent successful in intervention, the expected reduction in accidents would be 1.090 FMs/100,000 flight hours. Using the TACAIR flight hours for FY98, the expected reduction in FMs would be 4.453 FMs. At an average cost of $22 million per FM for FY98 (Gaynor, 1999), that would be an approximate $98 million savings for that fiscal year.

An observation can be made concerning single point intervention using the current "Crew Resource Management" program effect on FMs. By FY94, the Navy had established a program to increase awareness of "Crew Resource Management" and had widely disseminated the program to all Naval squadrons to implement in their safety training programs. Taking the HFACS data and looking at the rates of "Crew Resource Management" from FY94 to FY97 (Figure 7), there has not been a significant decline in the rate of "Crew Resource Management." Looking at the accident data for FY98, one sees that the data is incomplete, and does not contain a full account of causal factors for the 12 FMs during FY98. The current (though incomplete) "Crew Resource Management" arrival rate of 1.23 FMs/100,000 flight hours is not significantly below the "Crew Resource Management" average of 1.412 FMs/100,000 flight hours from FY94 to FY97. In five years of intervention, no significant change in the rate of "Crew Resource Management" being cited as a causal factor in Naval TACAIR FMs has occurred.

The second viewpoint of intervention is that it is not sufficient at a single point, for HE needs to be considered as a complex web of interwoven causal factors (Figure 5).

The results of the analysis for the HFACS causal factors in TACAIR FMs from FY90 to FY97 highlight one significant causal factor, "Adverse Mental State." Taking the two statistically significant combinations of causal factors, the mean accidents/100,000 flight hours are listed in Table 10 along with a 50 percent intervention result. Consider the combination of "Adverse Mental State and Skill-Based Error" in Table 10. As an example, the Navy must develop a program to intervene at both these levels in combination. If the program is 50 percent successful, the expected reduction in accidents would be 0.727 FMs/100,000 flight hours. Using the TACAIR flight hours for FY98, the expected reduction would be 2.97 FMs. At an average cost of $22 million per FM for FY98 (Gaynor, 1999), that would be an approximate $65 million savings for that fiscal year.

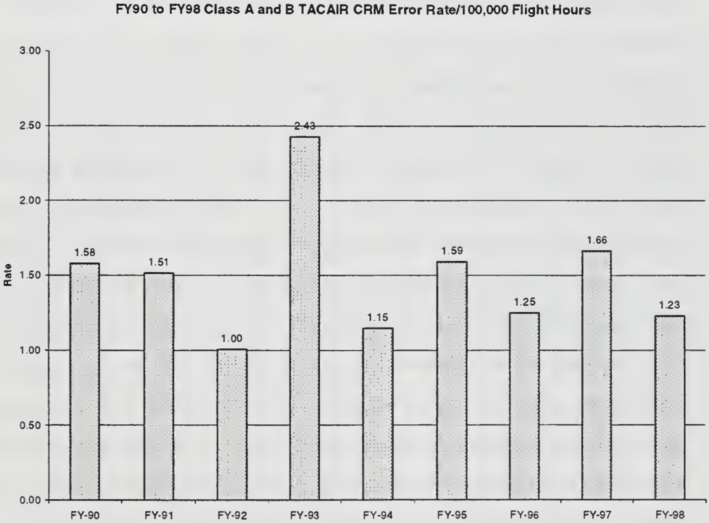


Figure 7. Crew Resource Management (CRM) arrival rate per 100,000 flight hours for FY90 to FY98. FY98 has incomplete data due to some MIRs not being fully completed for the year. Example: for FY94 CRM, HEs occurred in 1.15 FMs/100.000 flight hours.

Table 10. Mean accidents/100,000 flight hours predicted in simulation for significant combinations of causal factors.

	Mean/100,000 flight hours	50% reduction
Adverse Mental State/Skill-Based Error	1.453	0.727
Adverse Mental State/CRM	1.101	0.550

In reality, due to the complexity and interactions among different types of HE, predicting the reduction of HE is quite difficult. This complexity therefore should point to the development of a program that is as encompassing as possible. The program should cover many aspects of HE, while keeping the size of the program moderate and economical. The development time, maintenance requirements of the program and the time required to train aviators in the new program should be reasonable. The program should be a one- to two-hour program, providing annual or semi-annual presentations to aviators so they can maintain awareness of the program issues. Given the strong relationships exhibited by Adverse Mental State with the majority of the other causal factors in the HFACS taxonomy, focusing on an FM awareness program for Adverse Mental State would be a proper choice. Since Adverse Mental State is intertwined with so many other causal factors, intervention at Adverse Mental State would be expected to have the best chance of reducing FMs because of Adverse Mental State's important entanglements with multiple causal factors. This entangled relationship would give a FM reduction program that focused on Adverse Mental State the best chance of completely breaking the chain of events leading to a FM. Compared with an intervention program that focus's on a significant single causal factor, not having this entangled relationship with other causal factors, intervention at Adverse Mental State would be the obvious HE choice on which to focus in the development of a program to reduce human error FMs in Naval Aviation TACAIR.

APPENDIX A. CORRELATION MATRICES FOR MATRICES HFACSA, HFACSB, AND HFACSC

Correlation for data in: HFACSA

	A	B	C	D
A	1.000	-0.034	-0.117	0.079
B	-0.034	1.000	0.120	-0.066
C	-0.117	0.120	1.000	0.015
D	0.079	-0.066	0.015	1.000

Correlation for data in: HFACSB

	E	F	G	H	C	D
E	1.000	-0.241	0.183	0.080	0.074	-0.154
F	-0.241	1.000	-0.141	-0.048	-0.076	-0.158
G	0.183	-0.141	1.000	0.046	0.134	-0.023
H	0.080	-0.048	0.046	1.000	0.100	-0.046
C	0.074	-0.076	0.134	0.100	1.000	0.030
D	-0.154	-0.158	-0.023	-0.046	0.030	1.000

Correlation for data in: HFACSC

	I	J	K	L	M	N	O	P	Q	R	S
I	1.000	-0.241	-0.188	-0.140	-0.287	-0.018	0.180	0.067	0.041	-0.021	-0.040
J	-0.241	1.000	-0.217	0.020	0.037	-0.172	-0.001	-0.200	0.235	-0.047	0.082
K	-0.188	-0.217	1.000	0.195	0.109	0.623	0.146	0.001	-0.069	0.171	-0.007
L	-0.140	0.020	0.195	1.000	0.056	0.121	-0.103	-0.048	-0.076	0.045	0.008
M	-0.287	0.037	0.109	0.056	1.000	0.048	-0.175	0.082	-0.012	0.101	-0.120
N	-0.018	-0.172	0.623	0.121	0.048	1.000	0.170	0.022	-0.092	0.120	-0.000
O	0.180	-0.001	0.146	-0.103	-0.175	0.170	1.000	0.102	0.061	0.086	0.019
P	0.067	-0.200	0.001	-0.048	0.082	0.022	0.102	1.000	0.066	0.085	-0.063
Q	0.041	0.235	-0.069	-0.076	-0.012	-0.092	0.061	0.066	1.000	-0.093	-0.038
R	-0.021	-0.047	0.171	0.045	0.101	0.120	0.086	0.085	-0.093	1.000	0.182
S	-0.046	0.082	-0.007	0.008	-0.120	-0.000	0.019	-0.063	-0.038	0.182	1.000
T	-0.040	0.156	-0.050	-0.126	-0.010	-0.076	0.149	-0.087	-0.037	0.021	0.224
U	0.067	0.107	0.071	0.178	-0.007	0.097	0.167	0.072	0.005	0.085	0.081
V	0.160	0.093	-0.030	0.064	-0.109	-0.008	0.129	0.051	0.005	0.064	0.173
W	0.038	-0.054	-0.006	-0.104	-0.093	0.044	0.062	0.062	-0.132	-0.136	-0.025
X	0.066	-0.090	0.147	0.166	0.214	0.162	0.057	-0.020	0.086	-0.019	-0.046
Y	-0.048	0.127	-0.131	-0.070	-0.171	-0.043	0.023	-0.029	-0.032	-0.009	0.070

	T	U	V	W	X	Y
I	-0.040	0.067	0.160	0.038	0.066	-0.048
J	0.156	0.107	0.093	-0.054	-0.090	0.127
K	-0.050	0.071	-0.030	-0.006	0.147	-0.131
L	-0.126	0.178	0.064	-0.104	0.166	-0.070
M	-0.010	-0.007	-0.109	-0.093	0.214	-0.171
N	-0.076	0.097	-0.008	0.044	0.162	-0.043
O	0.149	0.167	0.129	0.062	0.057	0.023
P	-0.087	0.072	0.051	0.062	-0.020	-0.029
Q	-0.037	0.005	0.005	-0.132	0.086	-0.032
R	0.021	0.085	0.064	-0.136	-0.019	-0.009
S	0.224	0.081	0.173	-0.025	-0.046	0.070
T	1.000	-0.087	-0.011	-0.010	-0.030	0.054
U	-0.087	1.000	0.409	0.062	0.344	-0.029
V	-0.011	0.409	1.000	0.086	-0.023	-0.002
W	-0.010	0.062	0.086	1.000	-0.050	0.130
X	-0.030	0.344	-0.023	-0.050	1.000	-0.055
Y	0.054	-0.029	-0.002	0.130	-0.055	1.000

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APPENDIX B. S-PLUS SIMULATION CODE

```
hfacsprogram2 <-
function(mtrix,catvector,lambda,time,iterations,mishaps) {

   counter <- rep(0,iterations)
   poisson <- rep(0,iterations)
   counter.data <- 0
      for (i in 1:iterations) {

         #generate number of accidents E(count accidents) = lambda*time
         randompoisson <- rpois(1,lambda*time)
         poisson[i] <- randompoisson
         #generate random uniform selection of actual HFACS accident
         randomuniform <- round(runif(randompoisson,1,mishaps))
         #generate matrix of randomly selected accidents
         acc.data <- mtrix[randomuniform,]
         acc.matrix <- as.matrix(acc.data)
         solution.data <- catvector%*%t(acc.matrix)
         count.data <- sum(solution.data == sum(catvector))
         counter[i] <- count.data
      }
   print(mean(counter))
   print(quantile(poisson,.025))
   print(quantile(poisson,.975))
   print(quantile(counter,.025))
   print(quantile(counter,.975))
   data.frame(poisson,counter)

}
```

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APPENDIX C. MEAN AND 95 PERCENT CI FOR SIMULATION RUNS

Sets	*Mean*	*95% CI*
Singles		
O	8.901	(4, 15)
I	7.966	(3, 14)
J	7.223	(3, 12)
Q	6.508	(2, 12)
Y	4.071	(1, 8)
Doubles		
I – O	5.934	(2, 11)
Q – O	4.596	(1, 9)
K – O	2.658	(0, 6)
W – O	2.496	(0, 6)
N – O	2.193	(0, 5)
S – O	2.133	(0, 6)
T – O	1.321	(0, 4)
V – O	0.846	(0, 3)
V – I	0.830	(0, 3)
V – J	0.764	(0, 3)
U – O	0.755	(0, 3)
P – O	0.642	(0, 3)

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APPENDIX D. CAUSAL FACTOR RATE/100,000 FLIGHT HOURS

FY	A	E	I	J	K	F	L	M	B	G	N	O	P	H	Q	R	C	S
90	3.95	3.63	2.84	2.37	0.47	1.42	1.11	0.47	3.00	2.21	0.47	2.21	0.16	1.58	1.58	0.00	1.42	1.26
91	3.48	3.33	1.67	2.12	1.06	1.67	1.21	0.61	2.73	2.12	0.45	1.97	0.00	1.51	1.51	0.00	1.21	0.76
92	2.51	2.51	1.51	1.67	1.17	0.67	0.17	0.50	2.34	2.18	1.00	1.84	0.33	1.17	1.00	0.33	1.17	0.67
93	3.99	3.81	2.08	2.43	1.04	1.56	1.21	0.35	3.99	3.29	0.87	2.95	0.35	2.60	2.43	0.35	1.56	1.04
94	1.72	1.72	0.96	1.15	0.19	0.19	0.00	0.19	1.34	1.15	0.19	1.15	0.38	1.15	1.15	0.00	0.19	0.00
95	3.18	3.18	1.99	1.59	1.19	1.19	0.60	0.79	2.58	2.38	0.40	2.38	0.00	1.59	1.59	0.00	0.79	0.60
96	3.54	3.34	2.50	1.04	0.42	0.83	0.63	0.63	3.13	3.13	1.25	2.92	0.00	1.46	1.25	0.21	1.46	0.83
97	2.85	2.85	2.14	0.95	0.71	0.47	0.00	0.47	2.85	1.90	0.71	1.66	0.24	2.14	1.66	0.47	0.71	0.71
98	1.72	1.72	0.74	1.23	0.25	0.00	0.00	0.00	1.48	0.98	0.00	0.98	0.00	1.23	1.23	0.00	0.25	0.25

FY	T	U	V	D	W	X	Y
90	0.32	0.00	0.16	1.90	0.63	0.00	1.42
91	0.76	0.00	0.15	1.67	1.21	0.00	0.76
92	0.17	0.33	0.33	1.17	0.50	0.00	0.84
93	0.17	0.52	0.69	2.60	1.91	0.00	1.56
94	0.19	0.00	0.00	0.38	0.19	0.00	0.38
95	0.20	0.20	0.20	1.19	0.40	0.00	0.99
96	0.42	0.21	0.21	1.67	1.25	0.21	1.25
97	0.24	0.24	0.24	1.19	0.95	0.00	0.24
98	0.00	0.00	0.00	0.98	0.49	0.00	0.49

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APPENDIX E. KEY TO HFACS CODING A, … ,Y

Coding	HFACS Causal Factor
A	Unsafe Acts
B	Preconditions for Unsafe Acts
C	Unsafe Supervision
D	Organizational Influence
E	Errors
F	Violations
G	Substandard Conditions of Operators
H	Substandard Practices of Operators
I	Skill-Based Errors
J	Decision Errors
K	Perceptual Errors
L	Infraction
M	Exceptional
N	Adverse Physiological State
O	Adverse Mental State
P	Physical/Mental Limitation
Q	Crew Resource Management (CRM)
R	Personal Readiness
S	Inadequate Supervision
T	Planned Inappropriate Operations
U	Failed to Correct Problem
V	Supervisory Violations
W	Resource Management
X	Organizational Climate
Y	Organizational Process

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APPENDIX F. EXCERPT FROM OPNAV 3750.6R (APPENDIX O) HFACS TAXONOMY

Human Factors Analysis and Classification System (HFACS)

Drawing upon Reason's (1990) concept of latent and active failures, a framework was developed to identify the "holes" called the Human Factors Analysis and Classification System (HFACS). HFACS describes four levels of failure: 1) Unsafe Acts, 2) Preconditions for Unsafe Acts, 3) Unsafe Supervision, and 4) Organizational Influences. A brief description of the major components and causal categories follows, beginning with the level most closely tied to the accident, unsafe acts.

1. Unsafe Acts

The unsafe acts committed by aircrew generally take on two forms, errors and violations. The first, errors, are not surprising given the fact that human beings by their very nature make errors. Consequently, aircrew errors are seen in most FMs – often as that last fatal flaw before a FM occurs. Violations, on the other hand, represent the willful disregard for the rules and typically occur less frequently. Still, not all errors are alike. Likewise, there are different types of violations. As such, the unsafe acts aircrew commit can be classified among three basic error types (skill-based, decision, and perceptual) and two forms of violations (infractions and exceptional). Each will be described in turn (Figure 2).

Using this simple classification scheme, the investigator must first decide if an unsafe act (active failure) was committed by the operator (aircrew, maintainer, etc.). If so, the investigator must then decide if an error occurred or a rule was willfully violated. Once this is done, the investigator can further define the causal factor as a specific type of error or violation as described below.

Error

Skill-based Errors. Skill-based behavior is best described as those "stick-and-rudder" and other basic flight skills that occur without significant conscious thought. As a result, skill-based actions are particularly vulnerable to failures of attention and/or

memory. In fact, attention failures have been linked to many skill-based errors such as the breakdown in visual scan patterns, task fixation, the inadvertent activation of controls, and the misordering of steps in a procedure, among others (Table 1). Consider, for example, the pilot so intent on putting bombs on target that he disregards his low altitude warning only to collide with the ground. Closer to home, have you ever locked yourself out of your car or missed your exit because your were either distracted, in a hurry, or daydreaming? These are all examples of attention failures that occur during highly automatized behavior. While on the ground they may be frustrating, in the air they can become catastrophic.

In contrast to attention failures, memory failures often appear as omitted items in a checklist, place losing, or forgotten intentions. For example, most of us have experienced going to the refrigerator only to forget what we came for. Likewise, it is not difficult to imagine that in emergency situations, when under stress, steps in boldface emergency procedures or radio calls can be missed. Even when not particularly stressed however, individuals have forgotten to set the flaps on approach or lower the landing gear.

Skill-based errors can happen even when no apparent attention of memory failure is present. The individual flying skill/techniques of Naval aviators differ from one pilot to the next. We have all known individuals that fly smooth and effortless and those who make every mission an adventure. It is the skill-based errors of the latter that often leads to FMs as well. The bottom line is that skill-based errors are unintended behaviors. That is, individuals typically do not choose to limit their scan patterns, forget a boldface procedure, or fly poorly – it just happens, unbeknownst to the individual.

Decision Errors. The second error form, decision errors, represent intentional behavior that proceeds as intended, yet the plan proves inadequate or inappropriate for the situation. Often referred to as "honest mistakes", these unsafe acts represent the actions or inaction of individuals whose heart is in the right place, but they either did not have the appropriate knowledge available or just simply chose poorly. Regardless of the outcome, the individual made a conscious decision.

Decision errors come in many forms, and occur for a variety of reasons. However, they typically represent poor decisions, improper procedural execution, or the misinterpretation or misuse of relevant information (Table 1). The bottom line is that for good or bad the individual made a conscious choice and elected to do what was done in the cockpit – unfortunately, in the case of FMs, it did not work.

Perceptual Errors. Not surprisingly, when your perception of the world is different then reality, errors can, and often do, occur. Typically, perceptual errors occur when sensory input is degraded or 'unusual', as is the case when visual illusions or spatial disorientation occurs (Table 1). Visual illusions occur when the brain tries to 'fill in the gaps' with what it feels belongs in a visually impoverished environment, like that seen at night or in the weather. Likewise, spatial disorientation occurs when the vestibular system cannot resolve your orientation in space and therefore makes a "best guess" – typically when visual (horizon) cues are absent at night or in weather. In either event, the individual is left to make a decision based on faulty information leading to and error, and often a FM. Likewise, it is often quite difficult to judge precise distance and closure between aircraft and the ground when relative cues like clouds or terrain features are absent. Consequently, aircrews are left to make control inputs based upon misperceived or absent information. Tragically, these sorts of errors often lead to midair collisions or controlled flight into terrain.

Violations

Routine/Infractions. Violations in general are the willful departure from authority that simply cannot be tolerated. We have identified two distinct types of violations (Table 1). The first, infractions, tend to be routine/habitual by nature constituting a part of the individual's behavioral repertoire. For example, the individual that drives consistently 5-10 mph faster than allowed by law. While certainly against the law, many folks do it. Furthermore, if you go 64 in a 55 mph zone, you always drive 64 in a 55 mph zone. That is, you 'routinely' violate the law. Commonly referred to as "bending" the rules, these violations are often tolerated and, in effect, sanctioned by supervisory authority (that

Table 1. Selected examples of Unsafe Acts of Operators (Note: this is not a complete listing)	
Unsafe Acts of Operators	
Errors	Violations
<u>Skill-based Errors</u> Breakdown in Visual Scan Delayed Response Failed to Prioritize Attention Failed to Recognize Extremis Improper Instrument Cross-Check Inadvertent use of Flight Controls Omitted Step in Procedure Omitted Checklist Item Poor Technique	<u>Routine (Infractions)</u> Failed to Adhere to Brief Violation of Naval NATOPS/Regulations/SOP - Failed to use RADALT - Flew an unauthorized approach - Failed to execute appropriate rendezvous - Violated training rules - Failed to adhere to departure procedures - Flew overaggressive maneuver - Failed to properly prepare for flight - Failed to comply with NVG SOP
<u>Decision Errors</u> Improper Takeoff Improper Approach/Landing Improper Procedure Misdiagnosed Emergency Wrong Response to Emergency Exceeded Ability Inappropriate Maneuver Poor Decision	<u>Exceptional</u> Briefed Unauthorized Flight Not Current/Qualified for Mission Intentionally Exceeded the Limits of the Aircraft Violation of Naval NATOPS/Regulations/SOP - Continued low-altitude flight in VMC - Failed to ensure compliance with rules - Unauthorized low-altitude canyon running - Not current for mission - Flathatting on takeoff - Briefed and flew unauthorized maneuver
<u>Perceptual Errors</u> Misjudged Distance/Altitude/Airspeed Spatial Disorientation Visual Illusion	

is, you are not likely to get a ticket going 64 in a 55). If however, the local authorities started handing out tickets for exceeding the speed limit on the highway by 9 mph (like is often done on military installations) then it is less likely that individuals would violate the rules. Therefore, by definition, if a routine violation/infraction is identified, one must look further up the supervisory chain to identify those that are condoning those violations.

Exceptional. Unlike routine violations, exceptional violations appear as isolated departures from authority, not necessarily indicative of an individual's typical behavior pattern nor condoned by management. For example, an isolated instance of driving 105 mph in a 55 mph zone, or in Naval Aviation, *flathatting*, is considered an exceptional violation. It is important to note that while most exceptional violations are heinous, they are not considered 'exceptional' because of their extreme nature. Rather, they are considered exceptional because they are neither typical of the individual nor condoned by authority.

2. Preconditions for Unsafe Acts

Arguably, the unsafe acts of operators can be directly linked to nearly 80 percent of all Naval Aviation FMs. However, simply focusing on unsafe acts is like focusing on a fever without understanding the underlying disease causing it. As such, investigators must dig deeper into why the unsafe acts took place. As a first step, we describe two major subdivisions of unsafe aircrew conditions, each with their specific causal categories. Specifically, they include the Substandard Conditions of operators (i.e., Adverse Mental States, Adverse Physiological States, and Physical/Mental Limitations) as well as those Substandard Practices they commit. Each are described briefly below.

Substandard Conditions of Operators

Adverse Mental States. Being prepared mentally is critical in nearly every endeavor, perhaps more so in aviation. As such, the category of adverse mental states was created to account for those mental conditions that affect performance (Table 2). Principle among these is the loss of situational awareness, task fixation, distraction, and *mental* fatigue due to sleep loss or other stressors. Also included in this category are personality traits and pernicious attitudes such as overconfidence, complacency, and misplaced motivation. For example, if an individual is mentally tired for whatever reason, the likelihood that an error would occur increases. Likewise, overconfidence, arrogance, and other pernicious attitudes will influence the likelihood that a violation is committed. While errors and violations are important causal factors, adverse mental states such as these are no less important, perhaps even more so, in the causal sequence.

Adverse Physiological States. The second category, adverse physiological states, refers to those medical or physiological conditions that preclude safe operations (Table 2). Particularly important to Naval Aviation are conditions such as spatial disorientation, visual illusions, G-induced loss of consciousness (G-LOC), hypoxia, *physical* fatigue, and the myriad of pharmacological and medical abnormalities known to affect performance. If, for example, an individual were suffering from an inner ear infection, the likelihood of spatial disorientation occurring when entering IMC goes up markedly. Consequently, the medical condition must be addressed within the causal chain of events.

Physical/Mental Limitations. The third, and final, category of Aeromedical Conditions, Physical/Mental Limitations, refers to those instances when the mission requirements exceed the capabilities of the individual at the controls. Physical/Mental Limitations can take many forms (Table 2). For example, at night our visual systems are limited by the capability of the photosensors in our eyes and hence vision is severely degraded. Yet, like driving a car, we do not necessarily slow down or take additional precautions. In aviation, this often results in not seeing other aircraft, obstacles, or power lines due to the size or contrast of the object in the visual field. Similarly, there are occasions when the time required to complete a task or maneuver exceeds human capacity. It is well documented that if individuals are required to respond quickly (i.e., less time is available to consider all the possibilities or choices thoroughly), the probability of making an error goes up markedly.

There are two additional instances of physical/mental limitations that need to be addressed; albeit they are often overlooked in most FM investigations. They involve individuals who simply are not compatible with aviation. For example, some individuals simply do not have the physical strength to operate in high-G environments or for anthropometric reasons simply have difficulty reaching the controls. In other words, cockpits have traditionally not been designed with all shapes, sizes, and physical abilities in mind. Likewise, not everyone has the mental ability or aptitude for flying Naval aircraft. Just as not all of us can be concert pianists or NFL linebackers, we cannot all fly

Naval aircraft. The hard part is identifying whether this might of played a role in the FM causal sequence.

Substandard Practices of Operators

Crew Resource Mismanagement. To account for occurrences of poor coordination among aircrew and other personnel associated with the safe conduct of the flight, the category of crew resource management was created (Table 2). This includes coordination both within and between aircraft, ATC, and maintenance control, as well as facility and other support personnel. Anywhere communication between individuals is required, the potential for miscommunication, or simply poor resource management, exists. However, aircrew coordination does not stop with the aircrew in flight. It also includes coordination before and after the flight with the brief and debrief of the aircrew. Literally volumes have been written on the topic, yet it continues to permeate both fixed-wing and rotary-wing aviation, as well as multi-crew and single-seat aircraft. The conscientious investigator must always be aware of the potential for poor CRM practices.

Personal Readiness. In aviation, or for that matter in any occupational setting, individuals are expected to show up for work ready to perform at optimal levels. For Naval Aviation however, personal readiness failures occur when individuals fail to prepare physically or mentally for flight. For instance, violations of crew rest requirements, bottle-to-brief rules, and self-medicating all will affect performance in the aircraft. It is not hard to imagine that when you violate crew rest requirements, you run the risk of mental fatigue and other adverse mental states. (*Note that violations that effect personal*

Table 2. Selected examples of Unsafe Aircrew Conditions (Note: this is not a complete listing)	
Preconditions for Unsafe Acts	
Aeromedical <u>Adverse Mental States</u> Channelized Attention Complacency Distracted Mental Fatigue Get-home-it is Haste Life Stress Loss of Situational Awareness Misplaced Motivation Task Saturation <u>Adverse Physiological States</u> G-Induced Loss of Consciousness Impaired Physiological State Medical Illness Physiological Incapacitation Physical Fatigue <u>Physical/Mental Limitation</u> Insufficient Reaction Time Visual Limitation Incompatible Intelligence/Aptitude Incompatible Physical Capability	Crew Resource Management Failed to Back-up Failed to Communicate/Coordinate Failed to Conduct Adequate Brief Failed to Use All Available Resources Failure of Leadership Misinterpretation of Traffic Calls Trans-cockpit Authority Gradient Personal Readiness Excessive Physical Training Self-Medicating Violation of Crew Rest Requirement Violation of Bottle-to-Brief Requirement

readiness are not considered "unsafe act, violation" since they typically do not happen in the cockpit, nor are they active failures with direct and immediate consequences)

Still, not all personal readiness failures occur as a result of violations of rules. For example, running 10 miles before piloting an aircraft may not be against any existing regulations, yet it may impair the physical and mental capabilities of the individual enough to degrade performance and elicit unsafe acts. Likewise, the traditional "candy bar and coke" lunch of the naval aviator may sound good but may not be sufficient to sustain performance in the rigorous environment of military aviation. Even cramming for exams may significantly impair your sleep and may in some cases influence your

performance the next day in the cockpit. While, there may be no rules governing such behavior, aircrew must be their own best judge. Certainly, additional education and physical exercise is a good thing when taken in moderation, but aircrew must always assess their condition objectively before manning the aircraft.

3. Unsafe Supervision

It is the experience of the NSC that often the FM causal chain of events can be traced back up the supervisory chain of command. As such, we have identified four categories of Unsafe Supervision: Inadequate Supervision, Planned Inappropriate Operations, Failed to Correct a Known Problem, and Supervisory Violations. Each are described briefly below.

Inadequate Supervision. The role of any supervisor is to provide the opportunity to succeed. To do this the supervisor, no matter what level he operates at, must provide guidance, training opportunities, leadership, motivation, and the proper role model. Unfortunately, this is not always the case. It is not difficult to conceive of a situation where adequate crew resource management training was either not provided, or the opportunity to attend was not afforded, to a particular aircrew member. Conceivably, his aircrew coordination skills would be compromised and if put into an adverse situation (an emergency for instance), he would be at risk for errors and potentially a FM. Therefore, the category Inadequate Supervision was created to account for those times when supervision proves inappropriate, improper, or may not occur at all (Table 3).

Planned Inappropriate Operations. Occasionally, the operational tempo and/or schedule is planned such that individuals are put at unacceptable risk, crew rest is jeopardized, and ultimately performance is adversely affected. Such operations, though arguably unavoidable during emergency situations, are unacceptable during normal operations. Therefore, we have created a second category, Planned Inappropriate Operations, to account for these supervisory failures (Table 3). Included in this category are issues of crew pairing and improper manning. It's not surprising to anyone that when two individuals with marginal skills are paired together, problems can, and often do, arise. With downsizing and the current level of operational commitments, it is difficult to

manage crews. However, pairing two weak or inexperienced aircrew together on the most difficult mission may not be prudent.

Failure to Correct a Known Problem. The third category of known unsafe supervision, Failed to Correct a Problem, refers to those instances when deficiencies among individuals, equipment, training or other related safety areas are "known" to the supervisor, yet are allowed to continue uncorrected (Table 3). For example, the failure to consistently correct or discipline inappropriate behavior certainly fosters an unsafe atmosphere, but is not considered a violation if no specific rules or regulations were broken.

Supervisory Violations. Supervisory violations, on the other hand, are reserved for those instances when existing rules and regulations are willfully disregarded by supervisors when managing assets (Table 3). For instance, permitting an individual to operate an aircraft without current qualifications or license is a flagrant violation that invariably sets the stage for the tragic sequence of events that predictably follow.

4. Organizational Influences

Fallible decisions of upper-level management directly effect supervisory practices, as well as the conditions and actions of operators. These latent failures generally revolve around issues related to resource management, organizational climate, and operational processes.

Resource Management. This category refers to the management, allocation, and maintenance of organizational resources, such as human, monetary, and equipment/facilities. The term 'human' refers to the management of operators, staff, and maintenance personnel. Issues that directly influence safety include selection (including background checks), training, and staffing/manning. Monetary issues refer to the management of non-human resources, primarily monetary resources. For example,

Table 3. Selected examples of Unsafe Supervision (Note: this is not a complete listing)	
Inadequate Supervision	Failed to Correct a Known Problem
Failed to Provide Guidance	Failed to Correct Document in Error
Failed to Provide Operational Doctrine	Failed to Identify an At-Risk Aviator
Failed to Provide Oversight	Failed to Initiate Corrective Action
Failed to Provide Training	Failed to Report Unsafe Tendencies
Failed to Track Qualifications	
Failed to Track Performance	Supervisory Violations
	Authorized Unnecessary Hazard
Planned Inappropriate Operations	Failed to Enforce NATOPS/Regs/SOP
Failed to Provide Correct Data	Failed to Enforce T&R Manual
Failed to Provide Adequate Brief Time	Authorized Unqualified Crew for Flight
Improper Manning	
Mission Not IAW with NATOPS/Regs/SOP	
Permitted Unnecessary Hazard	
Provided Inadequate Opportunity for Crew Rest	

excessive cost cutting, a lack of funding for proper and safe equipment and resources both have adverse effects on operator performance and safety. Finally, Equipment/Facility refers to issues related to equipment design, including the purchasing of unsuitable equipment, inadequate design of work spaces, and failures to correct known design flaws. Management should ensure that human factors engineering principles are known and utilized and that specifications for equipment and workspace design are identified and met.

Organizational Climate. Organizational climate refers to a broad class of organizational variables that influence worker performance (Glick, 1985). It can be defined as the "situationally based consistencies in the organization's treatment of individuals." (Jones, 1988). In general, organizational climate is the prevailing atmosphere or environment within the organization. Within the present classification system, climate is broken down into three categories- structure, policies, and culture. The term 'structure' refers to the formal component of the organization (Mintzberg, 1993). The "form and shape" of an organization are reflected in the chain-of-command, delegation of authority

Table 4. Selected examples of Organizational Influences(Note: this is not a complete listing)	
<u>Resource/Acquisition Management</u>	<u>Organizational Process</u>
Human Resources	Operations
Selection	Operational tempo
Staffing/Manning	Time pressure
Training	Production quotas
Monetary/Budget Resources	Incentives
Excessive cost cutting	Measurement/Appraisal
Lack of funding	Schedules
Equipment/Facility Resources	Deficient planning
Poor design	Procedures
Purchasing of unsuitable equipment	Standards
	Clearly defined objectives
<u>Organizational Climate</u>	Documentation
Structure	Instructions
Chain-of-command	Oversight
Delegation of authority	Risk Management
Communication	Safety Programs
Formal accountability for actions	
Policies	
Hiring and firing	
Promotion	
Drugs and alcohol	
Culture	
Norms and rules	
Values and beliefs	
Organizational justice	
Citizen behavior	

and responsibility, communication channels, and formal accountability for actions. Organizations with maladaptive structures (i.e., do not optimally match to their operational environment or are unwilling to change), will be more prone to accidents and "will ultimately cease to exists." (Muchinsky, 1997). Policies refer to a course or method of action that guides present and future decisions. Policies may refer to hiring and firing, promotion, retention, raises, sick leave, drugs and alcohol, overtime, accident investigations, use of safety equipment, etc. When these policies are ill defined, adversarial, or conflicting, safety may be reduced. Finally, culture refers to unspoken or unofficial rules, values, attitudes, beliefs, and customs of an organization. "The way

things really get done around here." Other issues related to culture included organizational justice, psychological contracts, organizational citizenship behavior, esprit de corps, and union/management relations. All these issues affect attitudes about safety and the value of a safe working environment.

Operational Process. This category refers to the formal process by which things are done in the organization. It is subdivided into three broad categories - operations, procedures, and oversight. The term 'operations' refers to the characteristics or conditions of work that have been established by management. These characteristics included operational tempo, time pressures, production quotas, incentive systems, schedules, etc. When set up inappropriately, these working conditions can be detrimental to safety. Procedures are the official or formal procedures as to how the job is to be done. Examples include performance standards, objectives, documentation, instructions about procedures, etc. All of these, if inadequate, can negatively impact employee supervision, performance, and safety. Finally, oversight refers to management's monitoring and checking of resources, climate, and processes to ensure a safe and productive work environment. Issues here relate to organizational self-study, risk management, and the establishment and use of safety programs.

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